FINAL REPORT

Developing Dynamic Reference Models and a Decision Support Framework for Southeastern Ecosystems: An Integrated Approach

SERDP Project RC-1696

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14. ABSTRACT
At Eglin Air Force Base (AFB), the refinement of reference models for longleaf pine (*Pinus palustris*) sandhills was undertaken to incorporate the temporal variation of ecosystems caused by disturbance and succession, as well as seasonal, interannual, or decadal variability. The research component involved resampling vegetation, fauna and soils in restoration and reference plots established by the Nature Conservancy in 1993. Next, two decision-support tools were expanded as a framework for assessing ecosystem status and trends for the federally endangered red-cockaded woodpecker (*Picoides borealis*; RCW) and the longleaf pine sandhill ecosystems on which this species depends. Specifically, vegetation field data was used to parameterize a dynamic modeling tool to generate predictive habitat maps. The maps were then used as landscape layers in an RCW population model to show how landscape change could affect RCW populations over a 50 year time frame. Lastly, a Decision Support Framework was completed to display real-time analytical results for monitoring data that were developed in the field portion of this study.

15. SUBJECT TERMS
Dynamic reference model, decision support framework, longleaf pine ecosystem restoration, red-cockaded woodpecker habitat, longleaf pine reference conditions, ecological monitoring, novel ecosystems, biodiversity

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Keywords

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List of Acronyms

AFB	Air Force Base
AIC	Akaike's information criteria
ANCOVA	analysis of covariance
ANOVA	analysis of variance
AUC	area under curve
BA	basal area
CCA	canonical correspondence analysis
CISMA	Coastal Invasive Species Management Area
CTA	classification tree analysis
DBH	diameter at breast height
DOD	Department of Defense
DSF	decision support framework
DSS	decision support system
ECM	ecological condition model
ESA	Endangered Species Act
FDR	false discovery rate
GA DNR	Georgia Department of Natural Resources
GIS	geographic information system
GLM	generalized linear model
GLMM	generalized linear mixed models
GPS	global positioning system
HSD	honest significant difference
LCC	landscape conservation cooperatives
LCCA	Longleaf Core Conservation Area
LPRP	longleaf pine restoration plot
LRT	likelihood ratio test
MCBCL	Marine Corps Base Camp Lejeune
MD	Mahalonobis Distance
MRPP	multi-response permutation procedure
MVA	multivariate analysis
NEPA	National Environmental Policy Act
NMDS	non-metric multidimensional scaling
PerMANOVA	permutational multivariate analysis of variance
PS	proportional similarity
QAIC	quasi-likelihood Akaike's information criteria
RCBD	randomized complete block design
RCW	red-cockaded woodpecker
RCW DSS	red-cockaded woodpecker decision support system
RF	random forest
SE	standard error
SERDP	Strategic Environmental Research and Development Program
SON	statement of need
SLR	sea level rise

SRE	surface range envelope
TNC	The Nature Conservancy
TST	time since transition
USFWS	United States Fish and Wildlife Service

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Abstract

Objectives

At Eglin Air Force Base (AFB), a the refinement of reference models for longleaf pine (*Pinus palustris*) sandhills was undertaken to incorporate temporal variation in ecosystems caused by disturbance and succession, as well as seasonal, interannual, or decadal variability. Next, we expanded two decision-support tools as a framework for assessing ecosystem status and trends for the federally endangered red-cockaded woodpecker (*Picoides borealis*; RCW) and the longleaf pine sandhill ecosystems on which this species depends. Specifically, study objectives were to: (1) quantify annual and decadal dynamics of reference longleaf pine sandhills to create practical and realistic benchmarks for vegetation and faunal restoration; (2) determine recovery rates of degraded sandhill ecosystems (vegetation, soils, fauna) over a 10-15 year period in response to hardwood removal treatments; (3) integrate 1 and 2 above into a dynamic habitat modeling tool for management of RCWs, which integrates with an existing population model to incorporate population and forest habitat feedbacks; (4) integrate 1 and 2 above into a Decision Support Framework (DSF) that allows the evaluation of monitoring data and landscape-scale ecological condition, while enhancing decision making.

Technical Approach

The technical approach to meet each objective included the following: First, six large (81-ha) plots that were intensively studied reference sandhills from an experiment led by The Nature Conservancy (TNC) from 1993-1999 were resampled. To capture a wider range of variation, all 1-ha high-quality reference plots identified in the extensive monitoring program at Eglin AFB were also sampled. Second, the rates of recovery in vegetation and faunal communities and soil processes 15 years post-restoration treatments were examined. Short-term (1-5 year) response of vegetation response to management actions across Eglin AFB were determined by comparing ecological monitoring plots with that of reference conditions. Third, expert opinion and field data from Eglin AFB was used to parameterize a dynamic habitat modeling tool in the program ST-SIM (henceforth, the "ST-SIM landscape model"). Predictive habitat maps produced by this tool were then used as landscape layers in the RCW population model to show how landscape change, including successional processes, disturbance and anthropogenic development could affect RCW populations. 4) Oracle database was used to operate a DSF to automate statistical analysis of ecological monitoring data for spatial and temporal trends in ecological condition, relative to dynamic reference conditions monitored at Eglin over time. The DSF integrates with the ST-SIM landscape model by supplying base data layers.

Results

Degraded longleaf pine ecosystems were found to move directionally towards the a priori reference sites with all of the restoration treatments. The reference conditions, however, also moved with a magnitude equivalent to the movement of restoration vectors. This reference movement highlights a fundamental challenge in our understanding of recovery in the context of a dynamic target. The reference sites in this study became more species rich, achieved greater abundance of understory plants, and showed greater evenness in response to a suite of changes from 1994 to 2011, including multiple fires, a longleaf pine mast event, and several hurricanes.

Faunal studies produced results that showed longleaf pine obligate species to be abundant across all recovering longleaf pine sites despite differences in structure (mainly oak [*Quercus* spp.] stem density) that were thought to preclude recovery in faunal communities. These results suggest that the range of reference conditions is broader than previously considered, furthering an understanding of the limits of subjective reference targets in a dynamic and variable ecosystem.

Forest dynamics modeling allowed for the results of community recovery to be incorporated into a state-and-transition model of longleaf pine communities. This model, built in the program ST-SIM, was developed in conjunction with another SERDP project and the NC State University team. We joined a demographic model created through the prior SERDP work, which models RCW population dynamics with an ST-SIM landscape model customized to simulate longleaf pine dynamics in response to habitat management and other landscape change at Eglin AFB over a 50-year timeframe. Lastly, the DSF was completed at Eglin AFB to display real-time analytical results for monitoring data that were developed in the field portion of this study.

Benefits

The Dynamic Reference Concept and associated tools developed as part of this project use longleaf pine ecosystems to understand the ecological trajectories of recovery and management in the context of larger scale changes to reference site conditions over longer time frames. This study not only places restoration success in a theoretical construct that helps plan and organize conservation in the context of an uncertain future, its data analysis also provides managers and scientists tools to understand changes in the context of conservation objectives.

1. Objectives

1.1 Relative to the Strategic Environmental Research and Development Program (SERDP) statement of need (SON)

This project addresses the SERDP statement of need for the development of science-based recovery objectives for ecological systems in the southeastern United States (SISON-09-01). Longleaf pine (*Pinus palustris*) sandhills are well-represented on military lands throughout the Southeast. These forests provide the primary habitat for the federally endangered red-cockaded woodpecker (*Picoides borealis*; RCW); however, managing these lands to assist in the recovery of the RCW represents a difficult challenge with the limited understanding of recovery processes in this habitat type. Ecological restoration of degraded sites requires the movement of these sites towards some established reference condition. Current restoration models fall short in developing a management endpoint or benchmark in a dynamic ecosystem. These benchmarks are often represented by static references that may or may not be representative of a truly dynamic system (Kirkman and Mitchell 2006). Reference conditions are usually defined by an understanding of some past condition that may no longer be possible due to a variety of anthropogenic and climatic changes (Jackson and Hobbs 2009, Seastedt et al. 2008). While these references are usually defined by experts (White and Walker 1997), they are often biased because of the rarity of the reference sites which do not necessarily capture the range of variation in environmental conditions (White and Walker 1997). Without a clearly defined reference that incorporates such dynamism, it is difficult to determine if a degraded site is moving in a trajectory towards recovery (Jackson and Hobbs 2009). We hypothesize that such reference conditions must be dynamic to properly assess restoration progress of a degraded site.

At Eglin Air Force Base (AFB), recovery of the RCW relies on habitat management consistent with the requirements of the mission. An improved tool for management is a decision support framework (DSF) to assess movement along Eglin's desired future trajectory that extends the dynamic reference model. Specifically, a DSF that predicts current and future RCW habitat driven by landscape configuration and forest structure, and receives automated analysis of ecological monitoring data for spatial and temporal trends in ecological condition relative to reference habitat is warranted.

Building upon the successful groundwork at Eglin AFB, we engaged in a three-pronged field study for the refinement of reference models for longleaf pine sandhills, with the recognition that these conditions will continue to change in the future. Next, we expanded two decision-support tools as a framework for assessing ecosystem status and trends for the RCW and the longleaf pine sandhill ecosystems on which this species depends. Specifically, study objectives were to: 1) quantify annual and decadal dynamics of reference longleaf pine sandhills to create practical and realistic benchmarks for vegetation and faunal restoration; 2) determine recovery rates of degraded sandhill ecosystems (vegetation, soils, fauna) over a 10-15 year period in response to hardwood removal treatments; 3) integrate 1 and 2 above into a Longleaf Forest Dynamic Modeling Tool for management of RCWs, by incorporating population and forest habitat feedbacks; 4) integrate 1, and 2 above into a DSF that allows the evaluation of monitoring data and landscape-scale ecological condition, while enhancing decision making.

1.2 Working hypotheses

Two working hypotheses were identified: (1) Patterns of response of vegetation and fauna to initial restoration treatments would differ 15 years post treatment from that of the early response to the restoration treatments. This scenario would develop if differing vegetation trajectories associated with the initial treatments had occurred following multiple and more frequent prescribed fire events. The underlying rationale was that initial removal of midstory hardwood trees might affect the rate of ground-cover response through reduced competition for light and increased fine-fuel loading and continuity, resulting in less patchy fire that would control further woody stem recruitment and encourage herbaceous vegetation. (2) Sampling reference conditions over a longer temporal scale than that of the initial experiment would reveal that reference sites identified in 1994 as attainable restoration goals were actually temporally dynamic. The ramifications of this situation would mean that incorporation of a broader range of reference conditions as restoration targets would help avoid a rigid guideline for projecting desired restoration goals.

2. Background

2.1 Environmental issue that the research addressed in terms of DOD and regulatory requirements

Military bases are significant reservoirs of regional biodiversity, in part by providing critical habitat for endangered species. Longleaf pine sandhill habitat is well-represented on military lands across the Southeast, including the vast majority of acreage on Ft. Bragg, Ft. Benning, Eglin AFB, Ft. Gordon, and Ft. Jackson. Longleaf pine sandhills are also critical habitat for the RCW. Recovery of the RCW is highly dependent on Department of Defense (DOD) facilities (U.S. Fish and Wildlife Service (USFWS) 2003), and accordingly, the recovery of this species is the highest conservation priority on several bases. Facilitating military mission activities while sustaining RCWs in compliance with the Endangered Species Act (ESA), represents the most significant ecological challenge on these installations.

Monitoring management impacts on habitat through time and understanding the relationship between habitat dynamics and RCW population demography is a critical need in meeting that challenge. This requires not only that management impacts on habitat recovery be understood, but also considered in the context of the ecosystem dynamics of reference conditions (Sutter et al. 2001). Thus, defining dynamic reference models for measuring ecological recovery remains an area of priority research for ecological monitoring and restoration (Schulte et al. 2006). In the Southeast, only a relatively few extant reference ecosystems can be found that represent the biologically diverse and least-disturbed remnant stands of longleaf pine sandhills (Kirkman and Mitchell 2006). However, large tracts of such stands are well-represented at Eglin AFB, and they provide a unique opportunity to develop science-based restoration and management recovery objectives for natural ecosystems on other military lands (Hiers et al. 2003). The lack of a measure of recovery towards dynamic benchmark conditions continues to limit realistic models of endangered species populations and habitat management.

2.2 Summary of past research and state of the science

2.2.1 Field – original The Nature Conservancy (TNC) project findings

- The initial TNC study was conducted at Eglin AFB from 1994-1998 with the goal of comparing ecosystem responses to various restoration treatments aimed at hardwood reduction.

- Reference plots, established in 1994 were situated on sandhills in the western half of Eglin AFB and are in close proximity to bombing ranges that resulted in a regular fire regime since the 1960s and 1970s due to live fire ignition. Relative to other sandhill sites on the base, these sites were characterized by lower canopy cover, greater basal area of longleaf pines, and greater cover of graminoids, forbs and legumes.

- The original study was implemented as six randomized complete blocks with restoration treatments of burning, herbicide application (ULW form of hexazinone at a rate of 2.44 kg/ha), mechanical removal (felling/girdling) of hardwoods and untreated controls. These blocks extended across the northern portion of Eglin AFB. Each treatment was randomly assigned and applied to an 81-ha plot within each block.

  Major findings of this study were:

  a. Understory cover, herb-layer arthropods, and breeding birds were the key elements that responded when fire was included in the management treatment.

  b. The similarity of the herbicide and felling/girdling plots to the reference plots increased following fuel reduction fires.

  c. Plant species densities, soil and litter arthropods, and soil chemistry contributed weakly or not at all to the evaluation of restoration success.

  d. Indicators of restoration success generally increased after fire, although breeding birds responded mainly to a reduced midstory structure.

e. Significant variables identified as potential indicators of restoration success included: the cover of bare ground, fine litter, graminoids, and lichens; the densities of graminoids, legumes, and non-legume forbs; the density of longleaf pine >1.4 m tall (4.6 ft); the densities of the arthropods *Sminthurus* sp. 1, *Jikradia olitoria*, *Empoasca* spp., *Erythroneura* spp., and *Metcalfa pruinosa*; the detection rates of RCW, southeastern American kestrel (*Falco sparverius paulus*), Bachman's sparrow (*Aimophila aestivalis*), brown-headed nuthatch (*Sitta pusilla*), Carolina chickadee (*Poecile caroliniensis*), northern bobwhite (*Colinus virginianus*), northern cardinal (*Cardinalis cardinalis*), and tufted titmouse (*Baeolophus bicolor*); and the capture rates of six-lined racerunner (*Aspidoscelis sexlineata*), eastern fence lizard (*Sceloporus undulatus*), and eastern narrowmouth toad (*Gastrophryne caroliniensis*). Most of these indicators increased following treatments; indicators that decreased significantly after hardwood reduction to more closely resemble reference plots were fine litter, lichen, longleaf pine, tufted titmouse, and eastern narrowmouth toad. The decrease of Carolina chickadee and northern cardinal detection rates after hardwood reduction was not significant. The indicators that increased were mainly responding to fire, although bird detection rates generally responded to any midstory reduction method.

- Since 1998, all experimental and reference sites have been frequently burned under the management of Eglin AFB.

2.2.2 RCW population response to restoration of habitat

In the southeastern United States, military bases provide critical habitat for RCWs, and the species' recovery is highly dependent on DOD facilities (U.S. Fish and Wildlife Service 2003). Although DOD is responsible for much of the recovery progress to date (Costa 2004), recovery on military lands is limited by: 1) a lack of understanding of how variability in habitat conditions influences RCW populations, particularly when sites vary from "average" conditions and management history, and 2) an unrealistically static view of RCW habitat. Military lands often represent more extreme conditions in habitat (e.g. Eglin's low productivity sandhill site types), landscape size and continuity (200,000+ ha), fire history (aggressive suppression followed by aggressive reintroduction of fire), and age (nearly half of the old-growth stands in the southeast are found in Eglin). The assumption of static habitat is false for healthy populations and is even more suspect when applied to recovering populations or to evaluations of the species' response to habitat manipulation and natural disturbances. Moreover, the development of a dynamic model that allows the evaluation of forest management efforts is critical when the landscape is also managed to support the military mission.

2.2.3 Monitoring program at Eglin

Eglin AFB managers have pioneered the development of an automated database that analyzes ecological data as an information tool for fire and wildlife management activities. Data from vegetation monitoring program (approximately 200 1-ha sandhills plots) have been sampled on a rotating schedule since 2000. The geographic information system (GIS) model provides Eglin natural resource managers with a simple, consistent, and easily shared method to evaluate the condition of longleaf pine forests without resource-intensive fieldwork. The model is run annually with updated inputs derived from satellite imagery to identify areas that experienced a change in condition class and to assess the cumulative impact of management

efforts. Most notably, areas that show a decline in Tier condition (e.g., move from Tier 1 to Tier 2) are used as high-priority inputs in Eglin's burn prioritization model (Hiers et al. 2003), which is used to prioritize fire management activities on the base. In addition, when proposed actions require an Environmental Impact Statement under the National Environmental Policy Act (NEPA), the model results are used to determine if an action will impact Tier 1 habitat. Through discriminant function analysis, the model initially showed 86% accuracy when predicting four tiers of ecological condition, ground-truthed using ecological monitoring data, but recent tests have shown a decline in accuracy. While the model has proven to be a useful tool for Eglin's natural resource managers, it does have limitations. Namely, the model inputs are subjectively weighted, imagery classification error is propagated through the model, and continuous model results are grouped into four discrete categories of condition. For reference models, spatial assessments, and population simulations to be fully integrated into decision making for military base management, the DSF must: 1) provide data feedbacks that improve monitoring of landscape change along a future desired trajectory, and 2) improve predictive power of simulations over time through monitoring.

3. Materials and Methods

3.1 Study area

The study plots are located across Eglin AFB in southern Santa Rosa, Okaloosa and Walton counties in the Florida panhandle Gulf Coastal Plain (Figure 1). Mean annual temperature from 1994-2012 was 18.9º C and mean annual precipitation was 179 cm (NOAA 2013). The study was conducted in xeric sandhills characterized by Typic Quartzipsamments (Lakeland series soils), which are deep and excessively drained sands (Overing and Watts 1989). The sandhills at Eglin AFB fall under the high pine characterization by Myers (1990), referring to the hilly undulating terrain dominated by an open longleaf pine canopy with a hardwood midstory composed of turkey oak (*Quercus laevis*), bluejack oak (*Quercus incana*), persimmon (*Diospyros virginiana*), and yaupon (*Ilex vomitoria*).

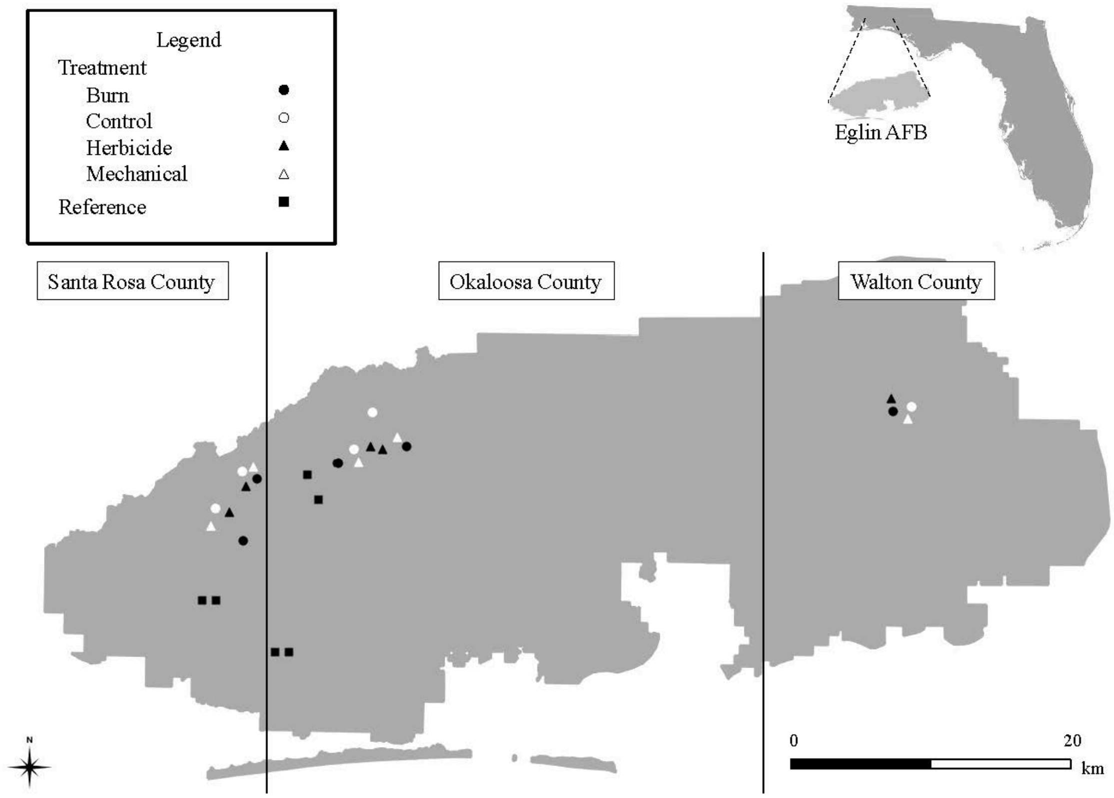


Figure 1. Plot location map displaying counties.

3.1.1 Experimental design

To evaluate the long term effectiveness of hardwood reduction treatments, we resampled vegetation and fauna in 2009-2011 in plots of a study initially established in 1994 (Provencher et al. 2000). In addition, we sampled soil characteristics of all treatment plots at two spatial scales. To determine long-term change in soil characteristics associated with the treatment, we quantified soil nutrient dynamics at the plot-scale, using a sampling design similar to that used in 1995. To explore the influence of treatments on spatial heterogeneity in soil nutrient dynamics, we examined soil characteristics at the scale of single trees. The 1994-1998 experimental design consisted of six randomized complete blocks of four plots each. Blocks were established in areas of continuous fire-suppressed longleaf pine stands that were characterized by a high density of large diameter hardwood trees and were large enough to contain four 81 ha plots (Provencher et al. 2000). The four plots in a block were randomly assigned to one each of four treatments: 1) control (no treatment), 2) burn (growing season burn), 3) herbicide (ULW®, application of the granular form of hexazinone), and 4) mechanical (mechanical removal of oaks (*Quercus* spp.) and sand pine (*Pinus clausa*); slash not removed). Treatments were applied in 1994 and 1995, and herbicide and mechanical removal plots were subjected to fuel reduction burns. In addition, six 81-ha reference plots (longleaf stands with a history of frequent fire) were established. These reference plots were burned throughout the duration of the 1994-1998 study. Plots are fully described by Rodgers and Provencher (1999).

A regular burn rotation (return interval of 3-4 years) was initiated for all blocks beginning in 1999. Block 5 of the 1994-1998 experiment was harvested for timber in 2007 and was excluded from all subsequent sampling.

3.1.2 Vegetation sampling

To maximize compatibility between 1994-1998 and 2009-2011 data sets, vegetation sampling followed the 1994-1998 study as closely as possible (Kirkman et al. 2013). Using the global positioning system (GPS) coordinates we relocated the 10 m x 40 m subplots established within each treatment plot in the 1994-1998 study and verified their positions by locating conduit that was placed in the ground during plot establishment (Figure 2). In 1994-1998 each treatment plot contained 32 subplots arranged in transects with either a 10 m (clumped) or 40 m (spaced) spacing between subplots. Results from the 1994-1998 study showed no effect of spacing within subplots; therefore we chose to sample only clumped subplots in 2009-2011 (sampling half of the original subplots). Vegetation in treatment plots were sampled in 2010. Reference plots were sampled in 2009 and 2011 (therefore in results referred to as 2010).

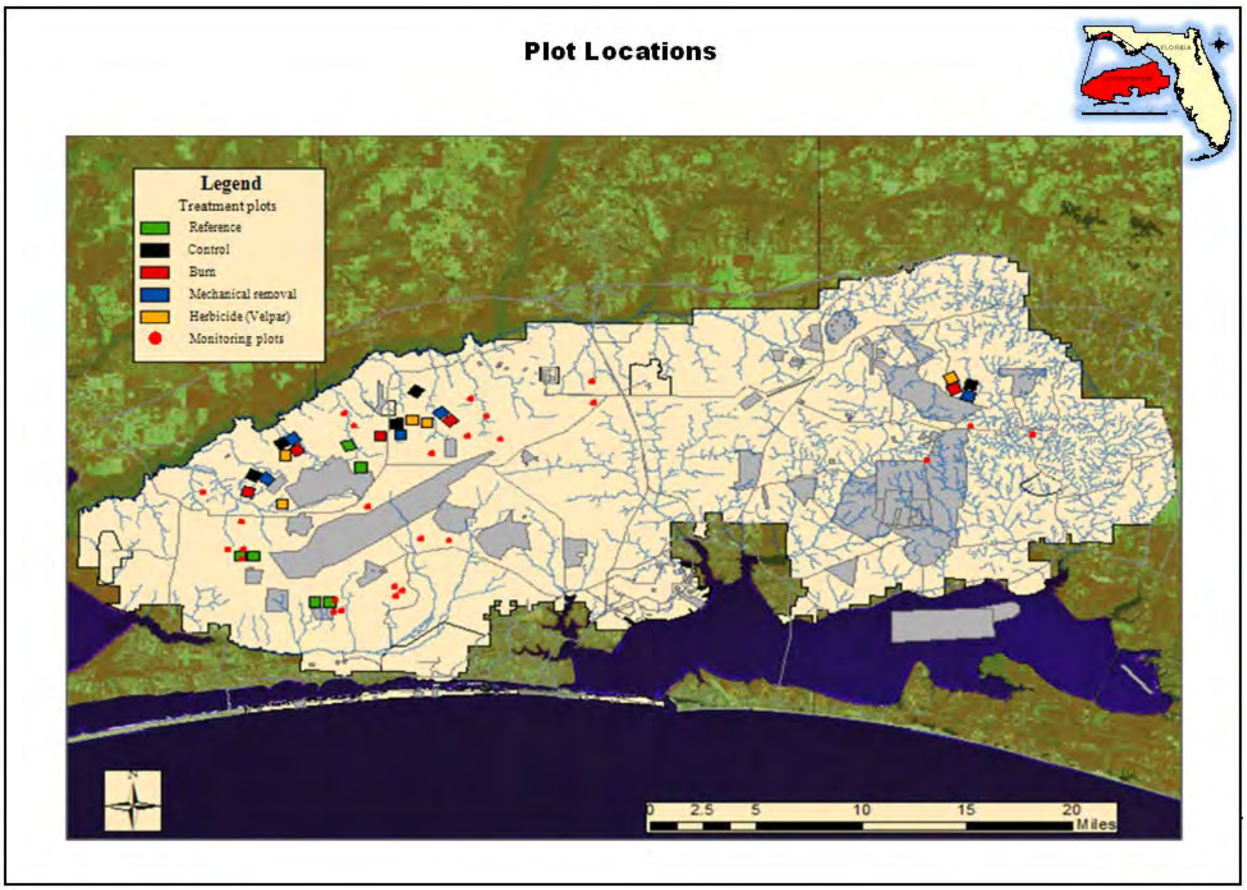


Figure 2. Plot location map of monitoring plots.

Trees

Trees were sub-sampled within each subplot by species. Longleaf pine trees were sampled January through February and all hardwoods were sampled March through June on an annual basis. We collected DBH (diameter at breast height) and height data on all trees >1.4 m. All longleaf pine adults (>1.4 m) were sampled throughout the subplot. Midstory trees were distinguished from overstory trees based on their DBH and followed Eglin AFB monitoring protocols. A pine tree was considered overstory if it was ≥ 10.16 cm DBH. An oak tree was

considered overstory if it was ≥ 16 cm DBH. Within each subplot all other species of trees were subsampled. Turkey oaks were sampled within two 5 m x 10 m sub-plots located at the ends of the 10 m x 40 m subplots. Other species were sampled in randomly selected longitudinal half of each 10 m x 40 m subplot. Longleaf pine juveniles (<1.4 m high) were counted along a random longitudinal half (5 m x 40 m) of each subplot (Figure 3). Stems of all other tree species <1.4 m high were counted in the ground cover sampling.

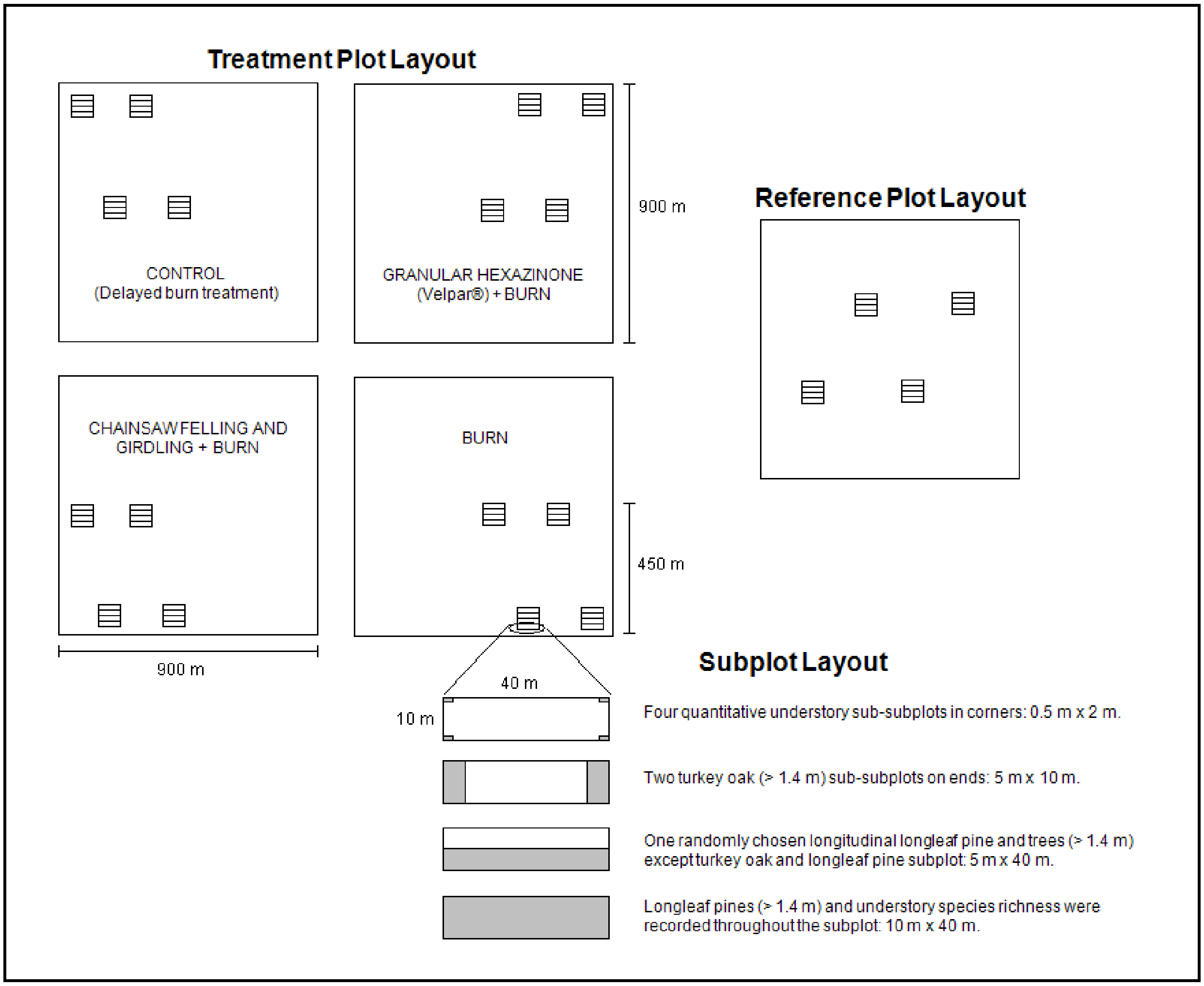


Figure 3. Vegetation sampling layout. Restoration subplot transects were located in corners farthest from other treatments to limit influence of adjacent treatments. Reference subplots were located in the center of the 81 ha plots. All vegetation was sampled in the same sub-subplots as the original study.

Ground cover

Ground cover sampling began in mid-August and was completed by the first week of November each year. To account for any late appearing or flowering species, those plots sampled in late August were revisited at the end of the sampling period. Ground cover was sampled in four 0.5 m x 2 m quadrats located in each corner of the subplots and included all species <1.4 m in height (Figure 3). In each quadrat, we recorded number of stems of all species. Plant

nomenclature followed Wunderlin and Hansen (2003). When a specimen lacked a key character for positive identification, we flagged it for identification on a return visit. Some species were combined as a morphospecies due to difficulty in separating them vegetatively in the field (Appendix B-1). Additionally, percent cover was estimated in each quadrat for nine ground cover vegetation categories; wiregrass (*Aristida stricta*) and pineywoods dropseed (*Sporobolus junceus*), all other grasses and sedges, forbs, lichens, woody species, bare ground, fine litter (fine organic litter and root masses), woody litter, and cryptobiotic crust (black form). To obtain species richness at the sub-plot level, we completed a 15 minute walk through each subplot to record any additional species not found in the four quadrats of that subplot.

Vegetation analyses

We examined the change in ground cover species composition from pre-treatment (1994) to 15 years post-treatment (2011) via non-metric multidimensional scaling (NMDS) ordination (Kruskal 1964) using the nmds function in the *labdsv* package (Roberts 2010). These analyses were performed using the R statistical environment (R Development Core Team 2011). To assess reference site change over time and to compare effectiveness among restoration treatments, we evaluated the similarity of vegetation to reference conditions before and after treatment and compared changes over time among treatment plots. First, we examined pre-treatment vegetation composition relative to 1994 reference conditions. We calculated a 90% confidence ellipsoid in three-dimensional ordination space to represent reference conditions. Then we compared pre- (1994) and post-treatment (2010) composition of the treatment plots in ordination space. We used multiple regression to evaluate the strength of the correlation between the NMDS ordination axes (n=3) and potential explanatory variables of burn history (the number of fires per plot prior to 1994 and between 1994-2010), the midstory hardwood density (number of stems/ha), and overstory hardwood density (number of stems/ha) per plot. Finally, we compared the change in reference conditions between 1994 and 2010 relative to vegetation composition using all six years of treatment data. We used Mahalonobis distance (MD) values converted to chi-square probabilities to determine if any treatment plots moved within the 90% confidence ellipsoid of reference conditions over time. We identified indicator species of reference and treatment conditions with indicator analysis (Dufrêne and Legendre 1997) using the *indval* function in the *labdsv* package.

For each of the ordinations, we excluded rare species (those that occur in less than 5% of the plots [minimum of 2 plots]) and then log transformed the abundance data (stems/ha) to prevent common species from dominating the dissimilarity metric. For all ordinations, we used the Bray-Curtis distance metric with a NMDS starting configuration that requested a 6-dimensional solution stepping down to a 1-dimensional solution. Goodness-of-fit diagnostics associated with Shepard plots (ordination distances plotted against community dissimilarity) were developed as verification of quality for each ordination.

We used permutational multivariate analysis of variance (PerMANOVA; Anderson 2001) to compare the restoration hardwood reduction treatments at the treatment scale and to facilitate interpretation of the NMDS ordination diagrams by examining the distribution (mean and variance) of the community ground cover abundance data. These analyses are limited to differences among treatments and do not consider the relationship to reference plots, given that reference sites are fixed on the landscape and were not included within the blocks of the experimental design. Specifically, we used the *adonis* function in the *vegan* package (Oksanen et al. 2011) to determine how variation is attributed to different treatments (Anderson 2001).

Block was used as the strata so that the permutations only occurred within each block and not across all units. To test for differences in the variance associated with distance measures of one or more treatment groups, we used a permutation test to examine the null hypothesis of no difference in dispersion between treatments.

To incorporate reference conditions that were not part of the randomized complete block design (RCBD) we used similarity indices to examine change in vegetation composition by treatments. We calculated proportional similarity (PS) (Brower et al. 1989) between each treatment plot and reference plot. PS was calculated as:

$$PS_{ij} = 1-0.5 \sum_{k=1}^{s}(| Pik - Pjk |)$$

where *P* is the proportion of species *k* in treatment plot *i* and in reference site *j* (Brower et al. 1989). The proportions are based on relative abundance for vegetation cover variables. This formula was calculated for every restoration plot (n=20), paired with each reference site (n=5), and averaged over all reference sites per restoration plot. PS will equal 1 if plots have the same species in equivalent proportions. RCBD analysis of covariance (ANCOVA) was used to test for restoration treatment effects using 1994 pre-treatment PS values as the covariate to adjust post-treatment data and to account for differences among treatments that existed prior to treatment application.

To examine trends in biodiversity among treatments over time at various scales we calculated species richness at the quadrat, subplot, plot, and treatment levels by treatment and year. We classified each species into one of three categories based on their association with early successional vegetation or reference conditions (ruderal, semi-weedy, or longleaf pine associate) and compared the species richness of these vegetation classes by treatment for 1994 and 2010 using RCBD ANCOVA. Evenness and average log abundance were calculated only at the treatment level because these variables are scalable with area. We calculated Pielous' evenness as: H/ln(S), where H is the Shannon diversity index and S is species richness. We calculated average log abundance as

$$\bar{n} = \frac{1}{S} \sum_{i=1}^{S} log_{10} N_i$$

where *S* is species richness and N_i is the number of individuals of each species (You et al. 2009). We tested restoration treatment effects with RCBD ANCOVA using 1994 pre-treatment species richness data as the covariate to adjust post-treatment data and to account for differences among treatments that existed prior to treatment application. Similarly, we compared mean log abundance among treatments by year and ground cover guilds (trees, shrubs, forbs, graminoids) as well as by individual species of tree seedlings and sprouts in the ground cover (Appendix B-2). Differences among treatment means were determined by Tukey multiple comparison tests for years in which treatments differed. Following the species diversity volume concept of You et al. (2009), we created 3-dimensional graphs of the biodiversity measures by treatment and block to illustrate how species richness, evenness and average log abundance simultaneously changed over time and by treatment. We used RCBD ANCOVA to compare these three biodiversity measures among treatments by year using 1994 values as the covariate in all analyses.

3.1.3 Faunal sampling

Faunal sampling took place in 2009 and 2010. Reptile sampling arrays were placed in treatment blocks 1-4 and reference blocks 1 and 3. In 2009, birds were sampled in blocks 1-4 and three reference sites. All five blocks and five reference sites were sampled in 2010. Four transects were walked in reference sites in 2009, otherwise sampling methods replicated those used in 1998-1999 (Provencher et al. 2002c). Bird transects were located in the corner of each

plot farthest from other treatments in restoration plots and in the center of reference plots (Figure 4).

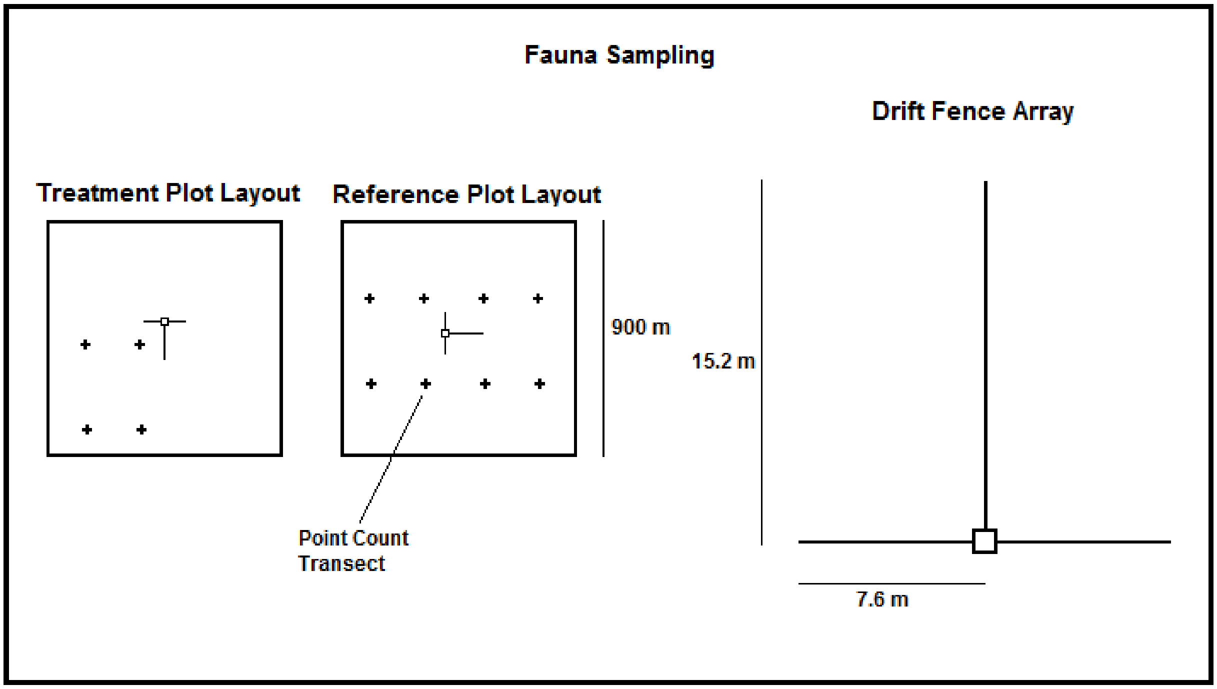


Figure 4. Fauna sampling plot layout. Like the vegetation subplots, bird point count transects were placed in corners farthest from other treatments to limit influence of adjacent treatments. Drift fence arrays were relocated in the same location as the original study.

Birds

Avian sampling included combinations of point counts and transects; specific methodology varied over the course of the study (see below). To maximize the likelihood of independence, all avian sampling in treatment sites occurred in the corners furthest from other treatment sites. Sampling within reference sites occurred within the center of the site. All samples were collected between approximately 0545 h and 1000 h. We rotated the order of sites sampled within a given morning to reduce bias associated with time; however, we were unable to sample sites in random order because of occasional restrictions on access to sites due to military training activities. Four treatment sites or 2-4 reference sites were sampled in a morning unless access was restricted due to military training. Two observers visited a site during each sampling occasion and walked along parallel transects 250 m apart from each other and approximately 450 m long. We recorded all birds estimated to be within the study site; we excluded birds that appeared to be only flying over the site. In the pre-treatment and early post-treatment study periods, the two observers took measures to remove any duplicate observations of the same individual bird (Provencher et al. 2002c); this was not completed in the late post-treatment period. This discrepancy was of no consequence to our results because of our focus on species-level data. Similarly, potential differences in observer skill are of little concern herein because of our emphasis on species-level data as well as our pooling of all observations within each sample during the early and post-treatment study periods (described below).

All 1994 pre-treatment sites were visited four times between 4 May and 18 July 1994, prior to hardwood removal treatments (Provencher et al. 2002c). Each time a treatment site was visited, two observers conducted eight minute point counts approximately 200 m apart along the transects (four total point counts each visit) and recorded all detected birds. Effort was doubled on reference sites, which resulted in eight point counts on four transects per site.

All 1998-1999 early post-treatment sites were visited six times each between 1 May and 30 June in 1998 and again in 1999 (12 total samples). Similar to the pre-treatment data collection, two observers sampled for birds simultaneously along parallel transects. However, in contrast to pre-treatment data collection, each observer conducted only one point count per visit; the point was at either the beginning or end of the transect, varying by visit. In addition, observers walked an entire transect (450 m) and recorded all birds detected. Walking a transect took approximately 22 minutes. With the addition of the eight-minute point count, each observer sampled birds for approximately 30 minutes per site (Provencher et al. 2002c).

For 2009-2010 late post-treatment sites, we attempted to sample four blocks and three reference sites four times each between 27 May and 13 July of 2009. Exceptions include one mechanical treatment site that was sampled only three times, a reference site that received a single visit, and a reference site that was sampled twice. Five blocks and five reference sites were sampled three times each between 11 May and 18 June 2010. Four transects were walked in reference sites in 2009, otherwise sampling methods replicated those used in 1998-1999.

Reptiles

To capture squamate reptiles (snakes and lizards), drift fence arrays (Campbell and Christman 1982) were placed at the center of each of 16 treatment sites and four reference sites. Hereafter, all captured squamates and turtles are collectively referred to as reptiles. Fences were made of aluminum flashing and sixteen 19 L pitfalls were placed along the fences of each array (30 m total of flashing per array). In the initial study, arrays were sampled from May-August 1997 and from April-August 1998 (Litt 1999, Litt et al. 2001, hereafter, early post-treatment); arrays were removed in 1998. In the second phase of the study, we reinstalled arrays in the same location at each site and reptiles were trapped from May-September 2009 and May-August 2010 (hereafter, late post-treatment). Late post-treatment, we added box traps to the center of the arrays as part of a separate study and slightly modified the array design (Burgdorf et al. 2005, Steen et al. 2010), but used the same length of drift fence and the same number of pitfall traps per array as in the original study.

All reptiles were individually marked early post-treatment but due to low recapture rates of most species (e.g., eastern fence lizard, 7.4%, broad-headed skink (*Plestiodon laticeps*), 6%, little brown skink (*Scincella lateralis*), 0%) and low recapture rates for these animals in general (e.g., Todd and Andrews 2008), we only individually marked six-lined racerunners late post-treatment (Steen 2011). We suggest data used in our analyses (i.e., the number of captures, irrespective of recapture status) are comparable to those used in other comparisons of capture rates (e.g., McCoy and Mushinsky 1999, Matthews et al. 2010). In addition, analysis of individual-level data of six-lined racerunners returned results consistent with capture-level data (Steen et al. 2013). We did not convert overall captures to captures per trap night because trapping effort was standardized across all treatments within each study period (e.g., Litt 1999, Steen 2011). We excluded box trap captures from the analysis since this method was not used in the initial study.

Bird analyses

We first conducted multivariate analyses because the number of sites sampled changed over time and to better visualize the change in bird assemblages within treatments. We treated each point count as an independent sample for the pre-treatment data (1994), such that four samples were created per visit. When necessary, we randomly removed from consideration half of the point counts conducted on reference sites to make sampling effort comparable to that of treatment sites. For both study periods following hardwood removal treatments, we pooled detections from both observers collected within a transect and point count, such that each time a site was visited one sample was created. We removed the first two samples in each of early post-treatment (1998-1999)) from consideration to make data from these years comparable to that of the other study periods. We created a presence/absence matrix where a species was given a score of "1" if detected within a sample and a score of "0" if not detected. Therefore, a species could have scored a maximum of 16 detections in a given site for the pre-treatment study period, eight for early post-treatment and seven for late post-treatment (2009-2010).

We used NMDS, (Clarke 1993), to graphically demonstrate differences in assemblages based on species identity and the number of times a species was detected (e.g., Kennedy et al. 2010). Given that some sites were not sampled in every time period and we were interested in how sites changed over time relative to reference conditions, we conducted two separate NMDS ordinations with Bray-Curtis (Sorenson) distances. The first ordination included pre-treatment and early post-treatment data. The second ordination included the early post-treatment and late post-treatment data. Statistical significance was determined by comparing observed stress to that obtained by Monte Carlo simulations. We used a multi-response permutation procedure (MRPP, Mielke and Berry 2001) to test the hypothesis that avian assemblages did not differ between treatments and reference sites. For each ordination, we removed species detected in only one sample to reduce the impact of rare and rarely detected species. Although rare species may be important to include in some analyses (e.g., Cao et al. 1998), removing rare species is a common strategy within NMDS (e.g., Kreutzweiser et al. 2005). We also did not include two aquatic species, the great blue heron (*Ardea herodias*) and common loon (*Gavia immer*). Ordinations and MRPP were completed using PC-ORD 4.0 (McCune and Mefford 1999).

If the MRPP indicated no significant difference between a given treatment and reference sites in either of the study periods following hardwood removal, we considered this evidence that the treatment was effective at restoring the avian assemblage. Treatment sites significantly different than reference sites were suggested to be ineffective at restoring the avian assemblage.

We identified indicator species for the different treatments and reference sites using methods described by Dufrêne and Legendre (1997). The indicator species analysis considered the number of detections and exclusivity of each species to sites within a treatment. Indicator species were assigned a value of 0-100. A 100 would indicate a species was observed in all sites of a given treatment and no other sites (Dufrêne and Legendre 1997). We used the presence/absence matrices described in the ordination section to identify indicator species. Statistical significance was determined with 1,000 Monte Carlo simulations. Indicator species analyses were completed using PC-ORD 4.0 (McCune and Mefford 1999).

As part of Eglin AFB's recovery plan for RCWs, artificial cavities were installed in pine trees between early and late post-treatment study periods (K. Gault, pers. comm. Jackson Guard). Therefore, we cannot interpret any change in their status as an indicator species between these study periods as due to the restoration methods used in this study. Red-headed woodpeckers (*Melanerpes erythrocephalus*) are kleptoparasites of RCW cavities (USFWS 2003) and may also

have benefitted from installation of artificial cavities; however, this benefit was likely relatively small, compared to that of RCWs, hence, we interpret change in parameters associated with this species as relevant to hardwood removal treatments.

The species we selected for occupancy modeling included those identified as indicators (as determined with indicator species analysis, above) of pre-treatment reference conditions. Of these species, we excluded RCWs and blue jays (*Cyanocitta cristata*). We excluded RCWs due to the additional management this species received and excluded blue jays due to their generalist habitat use and widespread distribution.

To standardize the methodology across study periods, we used only point count data and made each visit (i.e., sampling occasion) equivalent to the sum of the detections from two point counts. In the pre-treatment study period, eight point counts were conducted at each reference site per visit; we randomly removed four point counts. Since four point counts were conducted at treatment sites during each visit pre-treatment (and only two for the following study periods), we removed point counts conducted in the middle of the transect (half of all point counts pre-treatment) from analysis. In the first year of the late post-treatment study period, four point counts were conducted in each reference site; we randomly selected two of these for analysis. We again removed the first two surveys in both years sampled early post-treatment. We pooled data such that each time a site was visited, one sample was generated. As a result, we generated four samples for the pre-treatment data, eight samples for the early post-treatment sampling period, and seven samples for the late post-treatment sampling period. We then constructed a separate site x sample (i.e., survey) matrix for each indicator species chosen for analysis; a "1" was used to indicate whether a species was detected in a given sample and a "0" if it was not.

We used the multi-season model (MacKenzie et al. 2003) in Program PRESENCE to model occupancy (Hines 2010). In contrast to the single season model (MacKenzie et al. 2002), the multi-season model allows for changes in occupancy within a site. This is accomplished by distinguishing between primary sampling periods, between which occupancy may change, and secondary sampling periods, in which the population is considered closed to immigration, emigration, or extinction. We defined the pre-treatment data (1994), early post-treatment (1998-1999) and late post-treatment (2009-2010) as our three primary sampling periods. Each visit within a primary sampling period was considered a secondary sampling period.

We modeled occupancy in treatment and reference sites separately for each species. Our interest was in detecting changes in species occupancy; therefore, we considered detection probability a nuisance parameter. We first modeled detection probability for each species and used the combination of covariates that best predicted detection probability based on Akaike's Information Criteria (AIC), in successive occupancy models. Models used to evaluate detection probability in treatment sites included 1) constant detectability over all three study periods, 2) varying detectability by treatment type, 3) varying detectability by treatment type and each secondary sample, and 4) varying detectability by treatment type and primary sampling period. Models used to evaluate detection probability in reference sites included 1) constant detectability over all three study periods, 2) varying detectability by secondary sampling period and 3) varying detectability by primary sampling period.

We evaluated five occupancy models for each species in treatment sites, these models represented several hypotheses (Table 1) for how birds may respond to hardwood removal. We evaluated two occupancy models for each species in reference sites and used the combination of covariates producing the best estimate of detection probability for each species to model this parameter within occupancy models for that species. Models were ranked using AIC and we

considered models with ΔAIC values < 2 as important (Burnham and Anderson 2002). We did not correct AIC for small sample size (AIC_c) or for overdispersion, quasi-likelihood Akaike's information criteria (QAIC) because of problems obtaining numerical convergence. When more than one model had ΔAIC values < 2, we used model averaging to estimate occupancy probability. No formal method exists for determining goodness-of-fit for multi-season models. Therefore we used the single season model (MacKenzie et al. 2002) for the early post-treatment data with occupancy (Ψ) as a function of treatment type and detection probability varying by survey and treatment type to account for unmeasured heterogeneity (e.g., Adams et al. 2011). We conducted this analysis for data associated with treatment sites only.

Table 1. Models used to evaluate occupancy probabilities for select bird species detected from 1994-2010 to determine how they responded to hardwood removal on fire-suppressed longleaf pine sandhills. An "x" denotes the covariates best explaining detection probability, which varied by species (Table 5). PRD = primary sampling period, TRT = treatment.

Treatment Occupancy Models	**Hypotheses**
Ψ(PRD), γ (PRD),p(x)	Occupancy and colonization varied by primary sampling period
Ψ(TRT + PRD), γ (TRT + PRD), p(x)	Occupancy and colonization varied by primary sampling period and treatment type
Ψ(TRT + PRD), ε (TRT + PRD), p(x)	Occupancy and extinction varied by primary sampling period and treatment type
Ψ, γ(TRT + PRD), ε (TRT + PRD), p(x)	Colonization and extinction rates vary by primary sampling period and treatment type and are based on initial occupancy
Ψ, γ(TRT), ε(TRT + PRD), p(x)	Colonization varies by treatment type and extinction rates vary by primary sampling period and treatment type, both are based on initial occupancy
Reference Occupancy Models	
Ψ(.), γ (.),p(x)	Occupancy and colonization rates are constant
Ψ(PRD), γ (PRD),p(x)	Occupancy and colonization rates vary by primary sampling period

Reptile analyses

We calculated the Morisita-Horn similarity index for all reptiles at each site with EstimateS statistical estimation software version 8.2 (Colwell 2009). We selected this particular similarity index because it is statistically robust and relatively insensitive to low species richness and sample sizes (Magurran 2004). We first derived similarity values between reference sites in 1997-1998 and again for 2009-2010. Each site within a study period was then compared to the mean similarity index of reference sites for that study period. In other words, we determined

whether hardwood removal sites differed from reference sites more than references sites, on average, differed from each other. We calculated the Shannon index (Magurran 2004) to quantify diversity for each site in both study periods. This index is commonly used to describe reptile diversity (e.g., Greenberg et al. 1994, Michael et al. 2008).

We used a before-after control-impact study design (Stewart-Oaten et al. 1986) to compare reptile similarity and diversity with separate least squares means analyses of variance. We compared similarity and diversity on fire-suppressed controls and burn, mechanical, and herbicide treatments to that of reference sites in 1997-1998. We also compared similarity and diversity between treatments in 1997-1998 and in 2009-2010 to determine if reptile assemblages differed following a decade of prescribed burning. Finally, we compared similarity and diversity on all treatment sites to that of reference sites in 2009-2010. Our alpha level for all analyses was 0.10.

We conducted a single NMDS ordination, based on Bray-Curtis (Sorenson) distances, such that each site appeared in the ordination twice, once based on the 1997-1998 data and again based on 2009-2010 data. We used a MRPP (Mielke and Berry 2001) to determine whether a particular treatment (or reference site) was distinct from the other treatments within a given time period. Statistical significance was determined with Monte Carlo simulations. Analysis was implemented with PC-ORD v. 4.25 (McCune and Mefford 1999).

We assumed that control sites in 1997-1998 were representative of the pre-treatment condition at all treatment sites prior to hardwood removal. If the MRPP indicated no significant difference between a treatment and reference sites, we interpreted this to mean that the treatment resulted in conditions indistinguishable from those of reference sites. If the MRPP revealed a significant difference between conditions on treatment and reference sites, we considered the treatment as ineffective for restoration of reptile assemblages.

To determine if reptile abundance was associated with treatment type or reference sites while accounting for variation in habitat characteristics, we conducted a separate canonical correspondence analysis (CCA, ter Braak 1986) for each study period with species captured at least ten times. Within a CCA, a least squares regression of site scores (dependent variable, derived from weighted species abundance data) against environmental variables (independent variable) is conducted. In this manner, each site receives a score based on the regression equation (LC scores, Palmer 1993). An advantage of this technique is that it is unaffected by correlated environmental variables or skewed distributions (Palmer 1993) and may identify relationships other than those that are unimodal (ter Braak and Verdonschot 1995). The analysis allows production of a biplot that graphs sites and species in ordination space according to their association with environmental variables. Important environmental variables may be graphed onto the biplot as vectors, the length of which represents their relative importance (Methratta and Link 2006).

Environmental data included in the CCA were vegetative categories of grass, woody litter, fine litter, oak midstory, pine midstory, and oak overstory. Count data were square-root transformed and environmental variables were log-transformed prior to analysis (Palmer 1993). Statistical significance was determined via Monte Carlo simulations of eigenvalues and species-environment correlations. Analysis was completed with PC-ORD v. 4.25 (McCune and Mefford 1999).

We used a before-after control-impact study design and analysis of variance (ANOVA) (Stewart-Oaten et al. 1986) to compare the 1) number of marked adults and 2) number of marked juveniles among treatments and over time with SAS 9.2 (SAS Institute, Inc. 2008). Comparisons

of *a priori* interest were whether mean numbers of marked adults and juveniles within treatment sites were indistinguishable from those of reference sites for both study periods and whether these parameters changed over time. We set our alpha level at 0.05. If the number of marked adults and juveniles within a given treatment did not differ from those on reference sites, we assumed habitat condition was similar to that of references (i.e., provided evidence of a restored condition). To make inferences regarding how conditions changed over time, we assumed that conditions within control sites in 1998-1999 were representative of conditions at all treatment sites prior to hardwood removal. Because previous work has examined the short-term effects of hardwood removal on six-lined racerunners (Litt et al. 2001), our impact of interest was the reintroduction of prescribed burning on frequent-intervals over the long-term, which all sites, including controls, experienced after 1999.

3.1.4 Soil sampling

We carried out two studies of soil nutrient dynamics. To determine long-term change in soil characteristics associated with restoration treatments, we quantified soil nutrient dynamics and foliar nitrogen at the plot-scale, using a sampling design similar to that applied in 1994-1995. We will refer to this as the long-term dynamics study. To explore the influence of treatments on spatial heterogeneity in soil nutrient dynamics and vegetation composition, we examined soil characteristics at the scale of single trees. We will refer to this as the spatial heterogeneity study.

Study design and field sampling

The main objectives of the long-term dynamics study were three-fold. First, we determined the short-term effects (up to 3-years post treatment) of prescribed fire and hardwood removal treatments on soil C and N concentrations and pools in reference and fire-suppressed plots by analyzing unpublished data from the initial phase of the study (1994–1997). Second, we compared treatment effects between the initial phase and 2009 re-sampling to determine the long-term effects of restoration treatments on soil C and N concentrations and pools. Finally, we examined the long-term effects of restoration treatments on soil N and P mineralization rates, indices not measured in the initial phase of the study, by examining treatment effects present in 2009. To fulfill these objectives, we tested the effects of mechanical removal, herbicide application and burn-only on soil C and N and compared with the non-treatment (continued fire-suppression) and reference (frequently-burned and target for restoration) plots. All plots were measured prior to treatment in 1994, and were re-sampled two (1996), three (1997), and fifteen years (2009) after initial treatment.

In 1994, four soil cores (30-cm deep) were collected and mixed into one sample from the corners of each 10 × 40 m subplot (*i.e.*, $n = 4$ per plot) before treatments were applied (fall of 1994), two years after treatment (spring and fall of 1996) and three years after treatment application (spring and fall of 1997). Soil samples from all sampling events were transported back to the University of Florida and analyzed by the Analytical Research Laboratory at the University of Florida.

In June 2009, we revisited all restoration and reference plots. Prior to re-sampling, all plots burned several times between 1994 and 2009. All plots were also burned in prescribed fires between January and April 2009. In each plot, we sampled all four transects and for each transect, we sampled four 10 m spaced subplots and bulked the samples (*i.e.*, $n = 4$ per plot). Contrary to the original soil sampling (*i.e.*, 30 cm deep mineral soil core), at each sampling location, we collected

the litter and sampled the mineral soil separately from 0–10 cm and from 10–30 cm. Soil samples were kept on ice for transport back to the University of Florida and kept at 4 °C until processing.

Foliar samples were collected using a shotgun from mature longleaf pines in late December of 2010. A single tree was sampled from each subplot when mature trees were available (some subplots contained no mature longleaf pines). At least twelve samples were taken from each plot. This short window of opportunity limited sampling to 16 of the restoration plots (four complete blocks) and four reference plots (two complete blocks). Foliage was frozen upon collection and then transported to the University of Florida for processing.

In the spatial heterogeneity study, we characterized the spatial variability of soil biogeochemistry and understory vegetation in relation to individual longleaf pine trees in reference stands and the 15 year-old experimental manipulation of restoration treatments. Fifteen years after their establishment, we revisited the longleaf pine restoration plot (LPRP) and reference plots to determine whether the spatial patterning of soil processes and vegetation had been affected by the treatments. Our goals were to (1) characterize tree-based spatial patterning of soil characteristics and understory vegetation in the reference sites and experimental treatments; and (2) determine whether restoration treatments differed in their ability to restore spatial patterning to that seen in reference stands.

For the spatial heterogeneity study, we selected one block and two reference plots, and randomly located 36 canopy longleaf pine trees in August of 2009. Under each tree, we removed the litter and organic layers and sampled mineral soil (0 to 20 cm) at 1 m (near the trunk), 2 m, and 3 m (outside the tree crown) away from the tree, at three directions (0, 120, 240°) and bulked samples by distance from the tree. At each sampling location, a 0 to 20 cm depth volumetric soil sample was taken with a 2.5 cm diameter soil core. For this study we concentrated on the 0-20 cm depth because it is the area with the highest density of fine roots (Jones et al. 2003, Hendricks et al. 2006). Soil samples were kept on ice for transport back to University of Florida and kept at 4°C for < 1 week before processing.

In July 2011, we revisited the plots and the same 36 longleaf pine trees for a survey of the groundcover vegetation. Similar to the soil sampling, three line transects were placed radiating outwards from each tree in the same three directions (i.e., 0°, 120°, and 240°). A meter stick was placed perpendicular to the transect at 1 m, 2 m, 3 m and 4 m. Vegetation was classified by eight cover classes: wiregrass, other graminoids, legumes, other forbs, saw palmetto (*Serenoa repens*), pines, other woody species, and moss. Percent cover was estimated for each class crossing the meter stick plane at <1 m high: 0 = 0%; 1-5 = 3%; 6-10 = 8%; 11-15 = 13%; 16-25 = 21%; 25-50 = 38%; 51-75 = 68%; 75-95 = 85%; and 95-100 = 98%. Graminoids were defined as any grass or sedge except wiregrass. Woody species were defined as any groundcover vegetation with a woody stem except saw palmetto or pines (<1 m high).

Laboratory sample processing and analyses

All soil samples were homogenized by passing through a < 2 mm sieve and roots, twigs, and green vegetation were removed by hand. From each soil sample, a sub-sample was used to determine gravimetric moisture content, pH, total soil C and N, initial inorganic nitrogen (NO_3^- -N and NH_4^+-N), Melich-extractable phosphorus, and initial basal respiration. Soil basal respiration and inorganic nitrogen (NO_3^- -N and NH_4^+-N) were also measured after a 6-week aerobic laboratory incubation at field moisture and 25°C. Soil samples were adjusted with additional water during the incubation to maintain field moisture.

Total soil C and N were measured on subsamples of initial soil cores using a Costech ECS 4010 Elemental Analyzer (Valencia, CA) and calculated on a dry soil mass (%) and volume basis (e.g., g m^{-2}). Total (C and N) were calculated on a dry soil mass basis. pH measurements were made in aqueous suspensions (approximate soil:water ratio = 1:2).

To determine basal respiration, we placed one specimen cup filled with approximately 30 g fresh weight soil into a 1L Mason jar. We measured CO_2 production from the samples by sealing the Mason jars and measuring CO_2 accumulation in the headspace over a 96-h period. Air samples (10 ml) were taken from the jar headspace at time 0 and at hour 96 by syringe through a septum in the Mason jar lid, and injected into a Li-Cor 6252 CO_2 analyzer fitted with a calibrated injection port (Li-Cor, Nebraska, USA). Carbon flux rate was determined at the beginning of the incubation, after one week and after six weeks. Carbon dioxide production was expressed as µg C gdw^{-1} h^{-1}.

To determine melich P (double acid extractable P), soil samples were analyzed by extracting approximately 5 g of air-dried soil with 20 ml of double acid reagent (0.025 N H_2SO_4 + 0.05 N HCL). The solutions were shaken for 5 min at low speed and spun for about 5 min. Phosphorus extracts were determined using a microplate reader (BioTek Instruments, Inc., Winooski VT).

To determine N mineralization, soil samples were analyzed for initial and final pools of inorganic N (NH_4^+ -N and NO_3^- -N) by extracting approximately 10 g of field moist soil with 50 ml of 2.0 M KCL (Keeney and Nelson 1982). The solutions were shaken for 1 h and left to sit in an air-conditioned room (approx. 23°C) for 18-24 h and then filtered using a Whatman (GF/A) filter under vacuum. Ammonium and NO_3^- concentrations in extracts were determined calorimetrically using an Astoria-Pacific colorimetric autoanalyzer (Astoria, OR). Net rates of nitrification and N mineralization for the incubation period (i.e., 30 days) were calculated from the differences in initial and final inorganic N pools divided by the incubation time. All initial N pools and N rates were calculated on a dry soil mass basis (e.g., µg N gdw^{-1}) and volume basis (e.g., g N m^{-2}).

Foliage was removed from branches, dried at 60°C for 48-72 h, and ground to a fine powder on a Wiley Mill (Thomas Scientific, Swedesboro, New Jersey) with a #40 screen. Total foliar C and N were measured on a Costech ECS 4010 Elemental Analyzer (Valencia, CA).

Statistical analyses for long-term dynamics study

To account for differences in methodologies between the two-time period for C and CN ratios determination, we examined both datasets and compared relative differences within the datasets to test for the treatment effects. We used this approach because it has been frequently reported that dry combustion process results in higher C values than chemical oxidation with the Walkley-Black method (Bisutti et al. 2004). A factor of conversion is often used to compensate for the incomplete oxidation of organic C, but the use of this factor has the potential for serious error when estimating the C content of soils. Indeed, this factor of conversion is variable (1.35 to 14.1; Pribyl 2010) and has been shown to vary with soil type, mineralogy and soil depth (Perié and Ouimet 2008; Chatterjee et al. 2009). Similarly, dry combustion processes have also resulted in higher N values than the Kjeldahl method (Pereira et al. 2006; Dieckow et al. 2007). Thus, considering this limitation, we were unable to test for the effect of time on soil C, N and CN ratios.

Since the reference plots were not part of the five blocks, which include all restoration treatments, and were not spatially randomized, we could not include them in the generalized

linear mixed models (GLMM) analysis (see below). Instead, we used a nonparametric multivariate distance technique to compare selected soils characteristics of the restoration hardwood reduction treatments to each other and to reference conditions for the pre-treatment (fall 1994) and three post-treatment (spring 1996, 1997, and 2009) samplings. Three plots, a reference, herbicide and control, were missing post-treatment data for 2009. These three plots were excluded for all four time periods to ensure consistent comparison, resulting in a total of 101 samples for each time period. To account for the different scales and range of values in the three variables, each variable was relativized by its maximum value so that all variables ranged from 0 to 1. We used MRPP (McCune and Grace 2002) as implemented in PC-ORD v5 (McCune and Mefford 2006) with Euclidean distance, pairwise comparisons, $\alpha = 0.05$, and 1,000 permutations. MRPP is a distance-based analysis that enabled us to include the reference plots that were not part of the original RCBD. MRPP was run for each of the four time periods using the relativized data with five treatments, including reference, as the grouping variable. The false discovery rate correction (FDR; Benjamini and Hochberg 1995) was used to correct for multiple pairwise comparisons (Appendix B-3) using the statistical software R (R Development Core Team 2012).

Given that the MRPP analysis provides an integrated assessment of treatment differences, we also used univariate analysis to interpret the results of the MRPP. Thus, to compare the results (i.e. only top 30 cm of the mineral soil) from the late post-treatment (spring 2009) sampling with the early post-treatment samplings (spring and fall of 1996 and 1997), we used a GLMM (Bolker et al. 2009; Bates et al. 2012) to evaluate the effect of treatment (excluding the reference plots, see above) on total C and N concentrations with pre-treatment (fall of 1994) data as a covariate to account for differences among treatments that existed prior to treatment application. GLMM analysis was also used to evaluate the effect of treatment, depth and their interaction on soil bulk density, soil moisture content, pH, C and N (concentration and pool), melich P and N mineralization rates for the late post-treatment sampling (spring 2009). GLMM was used as well to test the effect of the interaction between treatment and time (spring 1997 vs. spring 2009) on soil C and N pools, and the effect of treatment on foliar C, N, ^{13}C and ^{15}N (spring 2009). All multiple comparisons of means were performed with Tukey adjustments. We computed the p-values with two methods. First, to produce a p-value for a particular fixed-effects term in a GLMM model, we use a likelihood ratio test (LRT). More explicitly, to compare the models, we first fit the model including the term to be tested using maximum likelihood, and then refit the model again without the term tested and compared both models using ANOVA (Crawley 2007, Zuur et al. 2009). We also produced p-values with Wald χ^2 tests, which are generally considered better than LTR for testing fixed effects with smaller sample sizes (Bolker et al. 2009). For simplicity and convenience and also because results from the two methods were highly similar, we presented only the results from the Wald χ^2 tests. All models were run in the statistical freeware R (R Development Core Team, 2012). The *lme4* package (Bates et al. 2012) was used for GLMM analysis, the *multcomp* package (Hothorn et al. 2008) used for multiple comparisons, and the *ggplot2* package (Wickham 2009) was used to produce figures.

Statistical analyses for spatial heterogeneity study

To test for the effects of treatment and distance from the tree on all soil and vegetation variables, we used ANCOVA, with treatment as the categorical variable and distance as the continuous variable (Amiotti et al. 2007, Zuur et al. 2005, Crawley 2007). If an ANCOVA has a significant interaction between treatment and distance, it will indicate that the slope (i.e.,

distance) of the soil or vegetation variable analyzed differs for different treatments. Multiple comparisons of means were performed with the Tukey HSD (honest significant difference) post hoc test. All results are reported as significant when $P < 0.05$. All statistical analyses were computed using R 2.14.2 (R Development Core Team 2011, Pinheiro et al. 2012).

3.2 Validation and Modification of the RCW Population Model (Version 2.0)

3.2.1 Background and objectives

As part of SERDP Research Project RC-1472, the Principal Investigator (J. Walters) and collaborators developed a tool (henceforth, the "RCW population model") to help DOD land managers (1) make efficient, scientifically informed decisions with regard to endangered species habitat and population management and (2) integrate conservation efforts with other DOD objectives, such as training and readiness planning. The tool that they ultimately created simulates the population dynamics RCW, an endangered species with significant populations on several DOD installations used heavily for training purposes in the southeastern United States. This tool is a spatially explicit, individual-based population model that incorporates the complex demography and ecology of the species with underlying habitat quality and operates as an add-in tool in ArcGIS Desktop ver10.0 (ESRI). The RCW population tool enables land managers to test hypotheses related to, for example, habitat restoration and land development or to identify locations where forest clearing will result in the least impact on RCW population dynamics over time.

Because the RCW population model is a critical component of the RCW Decision Support System (DSS) developed as part of this research project (RC-1696), we statistically validated the population model and made minor modifications following validation results. In this section, we describe the validation methodology and all program modifications ultimately made in response to the validation results for program version 2.0.

3.2.2 Validation methodology

It is necessary to validate any model in order to understand how closely that model approximates actual population dynamics, and validation is the clearest way to determine the robustness and reliability of demographic models used in important applications like conservation management and recovery planning (Beissinger and Westphal 1998, Akçakaya and Sjögren-Gulve 2000, Ralls et al. 2002). In order to validate our model, we compared simulation predictions with actual population dynamics for three RCW populations in the Sandhills of North Carolina, Marine Corps Base Camp Lejeune (MCBCL), and Eglin AFB (Figure 5; Figure 6). These populations were chosen because of the large volume of observational data available for comparison with simulation results.

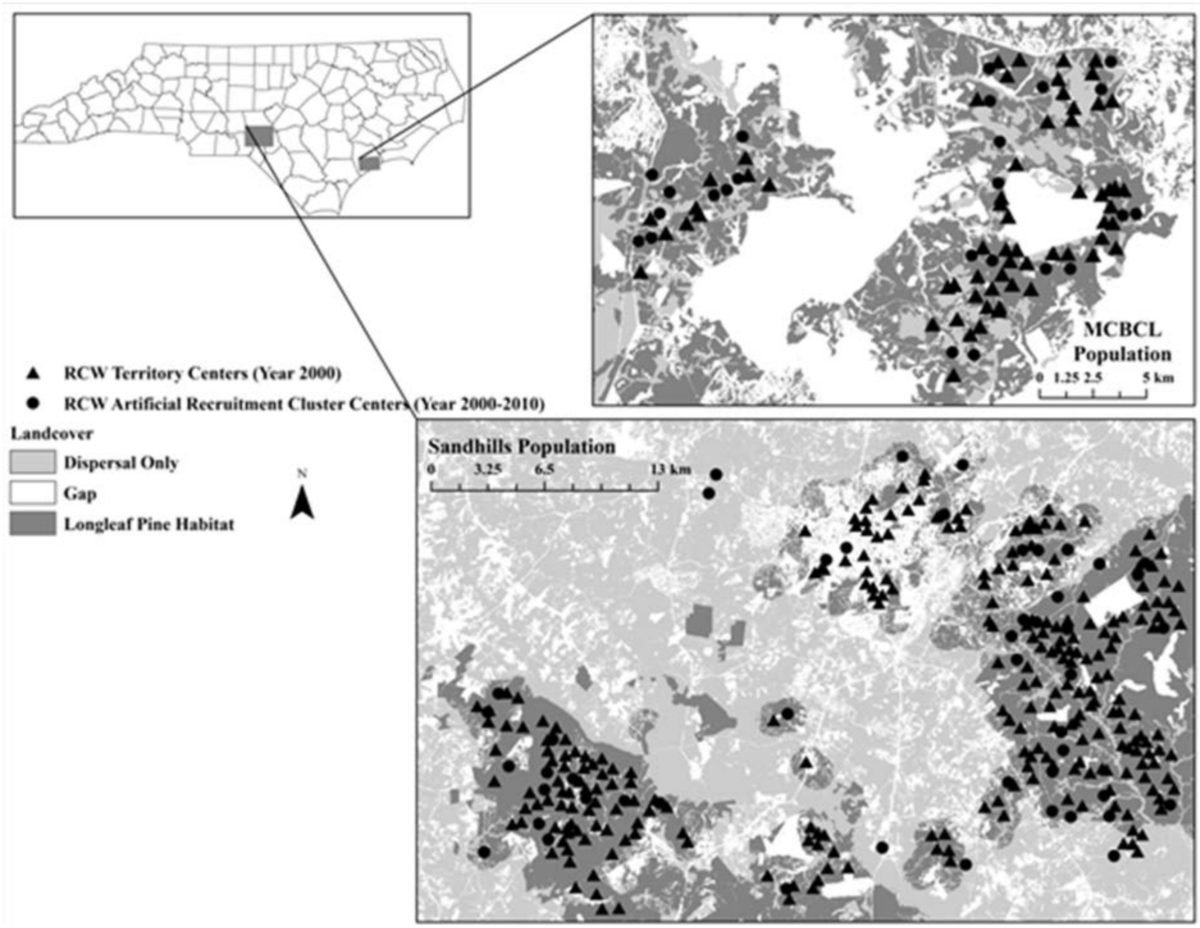


Figure 5. RCW territory centers in the year 2000 (triangles) and recruitment cluster centers added from 2000-2010 (circles) in the Sandhills and MCBCL study regions in North Carolina. The underlying landcover maps for each study region indicate whether an area acts as habitat suitable for reproduction (dark gray), habitat suitable only for dispersal (light gray), or as a gap that can limit dispersal for RCWs (white).

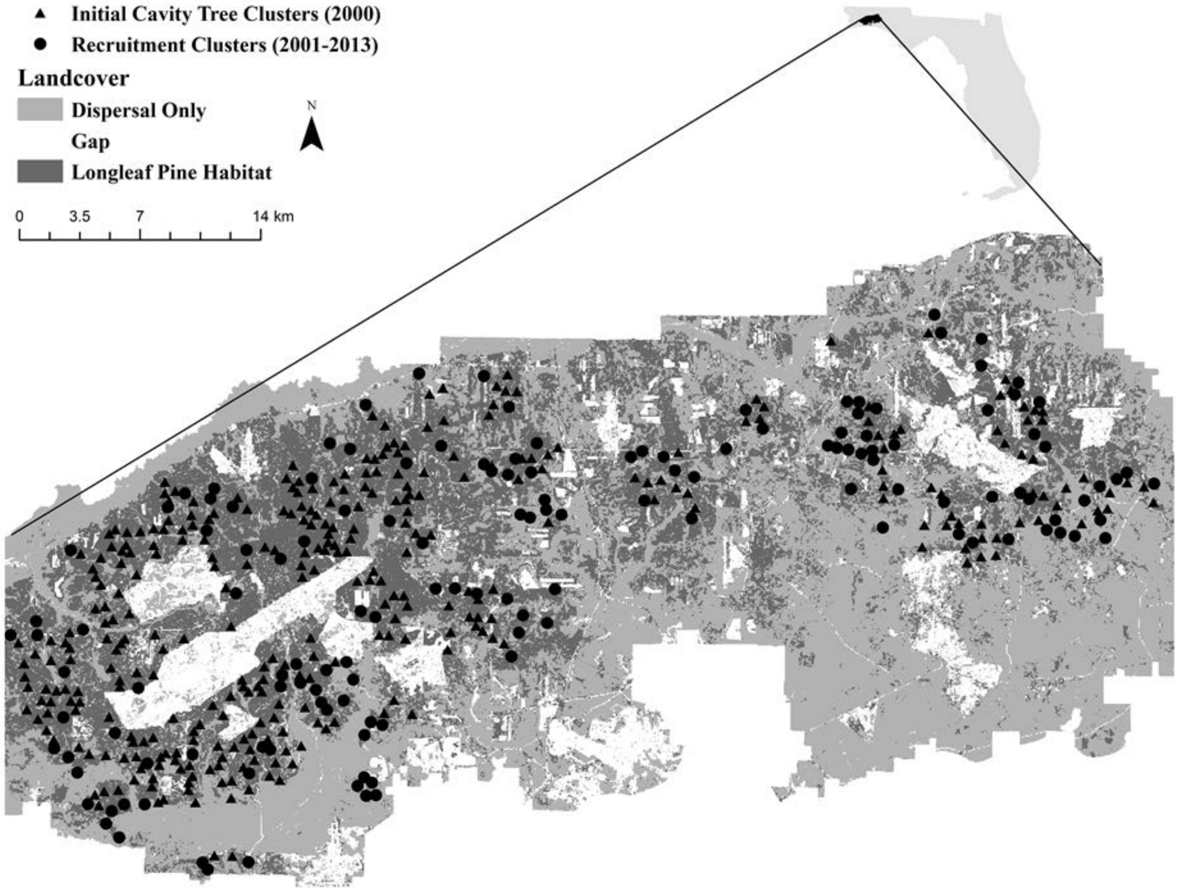


Figure 6. RCW territory centers in the year 2000 (triangles) and recruitment cluster centers added between 2000-2013 (circles) at Eglin AFB in the panhandle of Florida. The underlying landcover maps for each study region indicate whether an area acts as habitat suitable for reproduction (dark gray), habitat suitable only for dispersal (light gray), or as a gap that can limit dispersal for RCWs (white).

We created landscape layers for the three study areas that described landcover type, stand age, and site quality index for use as initialization layers within the RCW population model. The extent of the landscape used to represent the North Carolina Sandhills was within 5 km of all known RCW groups in the region, for a total area of 110,000 ha (Figure 5). Three sources of spatial data were used to create this landscape layer, including (1) forest stand data from US Army Fort Bragg and Camp Mackall (DOD), (2) forest stand data from the state of North Carolina (North Carolina Wildlife Resources Commission), and (3) the Southeastern GAP landcover dataset (http://www.basic.ncsu.edu/segap/ecosys.html), all representing landscape condition in the year 2000. The landscape used for simulations in the MCBCL study area encompassed the entire RCW population, which inhabits the main-side portion of the base (Figure 5). The same Southeastern GAP and forest stand datasets for the year 2000 were the primary data sources used to create the MCBCL landscape. Finally, the landscape layer for Eglin AFB was made using a landcover map classified from 2001 remotely sensed imagery by staff at the base (Figure 6). For all three study areas, we reclassified all landcover cells from the original classifications to the cover types recognized by the RCW modeling tool (Walters et al. 2011),

converted datasets from raster to polygon in the coordinate system “WGS 1984 UTM Zone 16N”, and merged separate datasets as needed (for the Sandhills and MCBCL study areas). Cavity tree cluster layers for the study areas were created using geographic coordinates for known RCW territory centers in the Sandhills, MCBCL, and Eglin AFB regions in the year 2000. In 2000, there were 259 RCW cavity tree clusters in the Sandhills region, 62 on MCBCL, and 337 on Eglin AFB (Figure 5; Figure 6). Territories known to contain either a solitary male or a breeding pair in 2000 were added to the model as occupied territories at the start of simulations (233 territories in the Sandhills, 57 on MCBCL, 295 on Eglin AFB), and all other “active” territories were added as vacant territories at this time (26 territories in the Sandhills, 5 on MCBCL, 42 on Eglin). These other active territories were either used for extra-territorial roosting by individuals residing in other territories or were added in the year 2000 as recruitment clusters and did not contain independent groups in that year. The RCW population model randomly chose group compositions for each cavity tree cluster based on the demographic sub-model selected. Current management activities for all three regions also included the use of recruitment clusters after the year 2000; we simulated the addition of 48, 24, and 143 unoccupied recruitment clusters for the Sandhills, MCBCL, and Eglin AFB study areas, respectively, in the same year that these clusters were added to the real landscape over course of simulations (Figure 5; Figure 6).

Finally, we parameterized the mean group size as 2.65 for the Sandhills, 2.9 for the MCBCL, and 2.5 for the Eglin AFB study areas in accordance with actual average group sizes observed in these regions (Walters unpublished data). We chose the “Sandhills” type locality for the Sandhills study area and the “Coastal” type locality for the MCBCL and Eglin AFB study areas.

Empirical values used to compare to the simulation outputs were extracted from existing databases collated during ongoing projects in the three study areas and spanned the years 2000 to 2010 inclusive for the Sandhills and MCBCL and 2000 to 2013 inclusive for Eglin AFB (Walters unpublished data; see Walters et al. 1988 and Walters 2004 for population monitoring methods). Simulations were initialized with population size and occupancy information specific to each population as observed in 2000. For validation purposes, we then compared mean values and their standard deviations with the actual population values for the number of occupied territories, population size (number of adults), and number of individuals in the solitary and breeding stage classes for the years 2001-2010 (model years 1-10) for the Sandhills and MCBCL study regions. Because population-related observations of the full Eglin AFB population were more limited, we only compared yearly means and standard deviations for the number of occupied territories for the years 2001-2013 (model years 1-13) for this study area. Following the methodology of McCarthy and Broome (2000), we calculated a standard deviate for each model output listed above for each year (2001-2010, 2013). In general, if a model’s output is accurate, then the standard deviates will have a mean equal to zero and a variance equal to one. We used a t-test to determine if the mean of the standard deviates for each model output was significantly different from zero and a chi-squared test to determine if the variance of the standard deviates was significantly different from one. We assumed significance at a level of $p < 0.01$. This method tests the accuracy of both the mean and variance in predicted model outputs. All data analyses were performed in R (R Development Core Team 2014).

3.2.3 Program modifications

In the first several iterations of the validation exercise, we consistently found that the predicted population sizes, number of occupied territories, and population compositions for all study areas differed significantly from those of the actual populations (results not shown). In these simulations, we found that simulated juvenile female RCWs were not able to find breeding vacancies in nearby clusters as readily as real RCWs on the landscape. As a result, the number of occupied territories and the number of breeding pairs (and ultimately, the number of offspring produced) were lower in simulations compared to actual population dynamics.

In response, we made minor modifications to how females move within the RCW population model to ensure that it simulated RCW population dynamics more accurately. In the previous version of the model, a juvenile female prospecting for breeding opportunities in the vicinity (i.e., within 6 km) of her natal territory never crossed open gaps in the landscape that were greater than 150 m. She could therefore not "see" or compete for breeding vacancies on territories separated from her natal territory by such a gap. In addition, the probability that a female floater (i.e., an adult without a territory) crossed gaps was dependent on the size of a given gap. A floater always crossed gaps $\geq$ 150 m, crossed gaps between 150 and 630 m with probability *p (*which was a declining function of gap length), and crossed gaps > 630 m with a 10% probability. However, these movement parameters for both female juveniles and floaters were found to be too restrictive, and we changed the minimum gap size from 150 m to 400 m. Thus, in the RCW population model version 2.0, prospecting juvenile females cross all gaps < 400 m and have a 10% probability of crossing any gap $\geq$ 400 m. Female floaters cross all gaps.

3.3 Development and validation of the ST-SIM model of longleaf pine ecosystem dynamics at Eglin AFB

3.3.1 Background and objectives

The longleaf pine ecosystem, dominant at Eglin AFB and throughout the southeastern United States, has declined in area by more than 97% (Frost 1993), making it the third most endangered ecosystem in the United States (Noss et al. 1995). The decline in this ecosystem has been primarily attributed to broad-scale patterns of logging and fire suppression following European settlement (reviewed in Ryan et al. 2013). Furthermore, studies have shown that, throughout the eastern and central United States, the most vulnerable tree species, and those experiencing the greatest population declines, have been fire-dependent species like longleaf pine (Hanberry et al. 2012, Hanberry 2014).

Fire suppression and general changes to natural disturbance regimes can have a number of consequences, including the reduction or loss of ecosystem services, an increase in landscape homogeneity, altered fire behavior, altered stand structure and community composition, and reduced biodiversity (reviewed in Ryan et al. 2013). In the longleaf pine ecosystem in particular, alteration of the ecosystem due to fire suppression has led to population declines and extirpations for many species, such as RCWs, across multiple taxa (Van Lear et al. 2005).

Restoration efforts, particularly prescribed burning, have been effective in improving the condition of longleaf pine ecosystems and the status of populations of endemic species at Eglin AFB (Provencher et al. 2001a, Provencher et al. 2002b, Provencher et al. 2002c). However, challenges and uncertainties remain with regard to the use of restoration techniques that reintroduce disturbance to longleaf pine ecosystems with a history of fire suppression (Varner et al. 2005, Ryan et al. 2013). In particular, the optimal type, frequency, intensity, size, periodicity, and duration of such restorative disturbance regimes is often unclear, although this knowledge can be critical for maintaining endangered species and their habitat (Warren and Buttner 2014).

Therefore, one of the primary goals of this Research Project was to develop a model that could be used to predict the dynamics of the longleaf pine ecosystem at Eglin AFB – with the ultimate goal of using this tool to evaluate the impacts of landcover modification (e.g., development projects), other landscape-mediated threats, and various management/restoration activities on RCWs.

In this section, we describe the landscape model that we developed to meet this objective. This model was constructed in the generic platform ST-SIM (Daniel and Frid 2011), which is a state-and-transition model that simulates future landcover conditions by considering interactions between successional processes, unplanned disturbances, and planned changes to the landscape. The use and parameterization of this model are fully described in a user's manual in Appendix D. The ST- SIM model is itself spatially explicit because it makes specific predictions about the state of the landscape (e.g., whether it is longleaf pine, hardwood, developed, etc.) at very specific geographic coordinates. Here, we discuss the basic states and transitions included in the baseline model for Eglin AFB as well as the results of model validation. The link between this landscape model and the RCW population model, in what we refer to as the "RCW DSS", as well as several applications of the coupled models are further described in Sections 3.4 and 3.5.

3.3.2 ST-SIM model parameterization for the Baseline Landscape model

In this section, we describe the landcover states, natural and management-related transitions that connect those states, and other important features of our landscape model of the longleaf pine ecosystem at Eglin AFB. These parameters were chosen based on expert opinion, the results of other components of this Research Project, and the published literature. In addition, these parameters comprise what we refer to as the "baseline landscape model", which describes current landcover states and management regimes. A user can modify many of the parameters described in this section to explore the impacts of landcover change and novel management regimes (see Section 3.5 for examples).

Landcover states

Non-longleaf pine states

In any ST-SIM model, each map unit (e.g., map cell, forest stand) in the total study area must fall within a discrete landcover class known as a "state". In our specific ST-SIM model of the longleaf pine ecosystem, we evaluated the landscape in 1-acre map cells and included states that were both characteristic of the landcover and vegetation types found throughout Eglin AFB and relevant to RCW habitat needs. As such, each state is associated with a specific RCW habitat suitability value (ranging from 1 to 5; Figure 7). We included major landcover classes for Young Longleaf Pine (0-15 years in age), Longleaf Pine (15-59 years and ≥ 60 years in age), Hardwood, Mixed, Sand Pine, Bare Land, and Water (Figure 7).

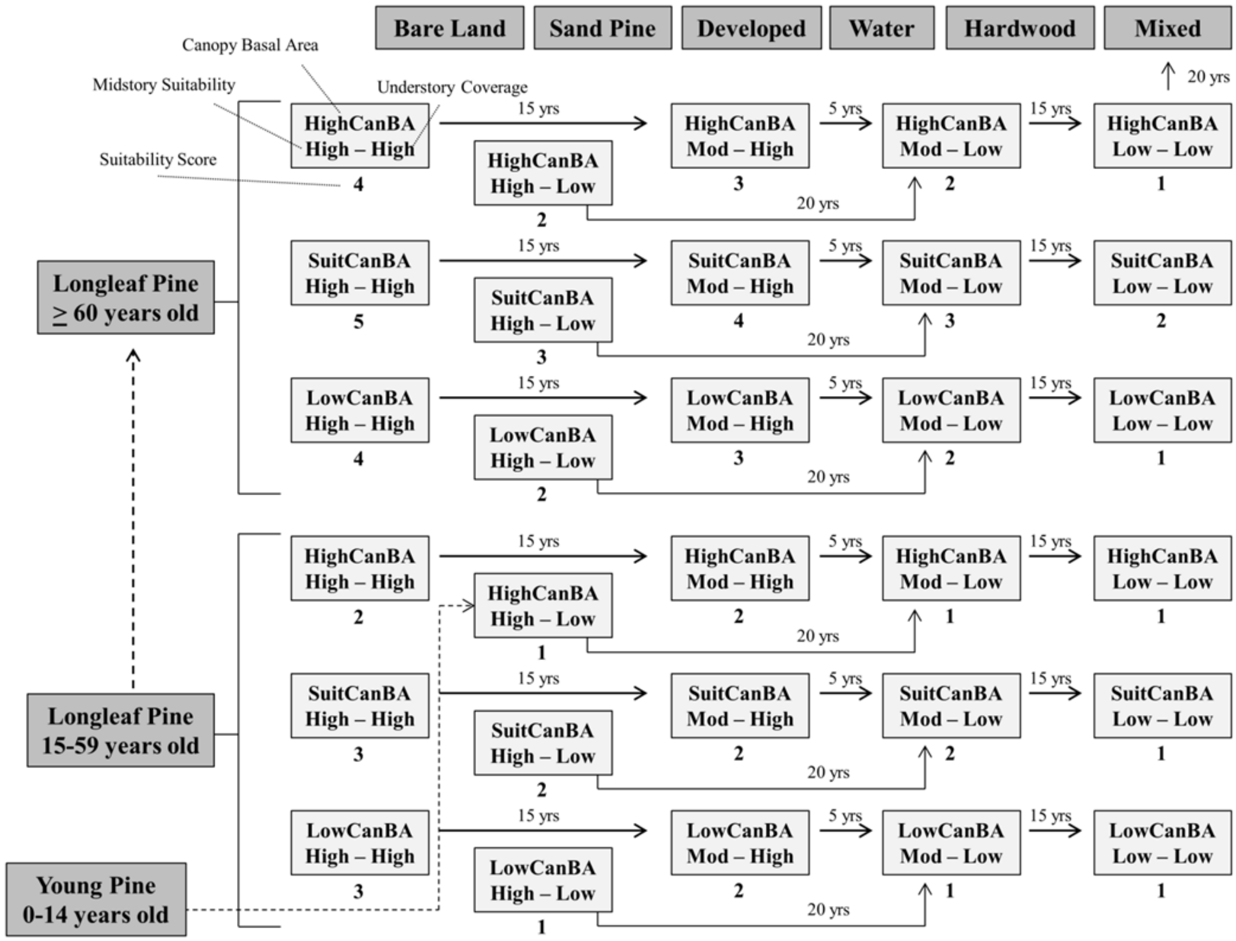


Figure 7. Landcover states in the ST-SIM landscape model and their connections through succession (solid arrows) and aging (dashed arrows). Landscape cells can age from any state in the Longleaf Pine 15-59 years class to the equivalent state within the Longleaf Pine ≥ 60 years class if stand age progresses past that age threshold during a simulation (arrows not shown). In this model, succession from one state to the next occurs if a disturbance (e.g., fire) has not occurred in that stand in 5-, 15-, or 20-year increments (period shown above succession arrows). Each state is associated with a RCW foraging habitat suitability score ranging from 1 (lowest suitability; all states except Longleaf Pine where noted) to 5 (highly suitable). See Table 2 for quantitative thresholds associated with qualitative states shown here.

The Longleaf Pine state is actually comprised of a series of states that are described later in this sub-section. Landscape cells categorized as Hardwood, Mixed, and Sand Pine contain forest stands where the majority of trees are hardwood species, an even mixture of pine and hardwood species, and sand pine, respectively. Landscape cells identified by the Developed state have been clear-cut, paved, or heavily altered for or by human use, and the Bare Land state describes areas with exposed soil (e.g., shoreline and cleared bombing ranges). Finally, the Water state includes areas covered by water bodies.

These landcover types are prevalent on Eglin AFB as well as in other regions where RCWs are found. With the exception of the Longleaf Pine states, we did not consider additional attributes for age or forest structure in other states, because, in some instances, forest structure is irrelevant (i.e., Developed, Water, Bare Land) or because, in other instances, RCWs use these landcover types infrequently irrespective of the forest structure (Hardwood, Mixed, Sand Pine; Hooper and Lennartz 1981, Repasky 1984, Porter and Labisky 1986, Bradshaw 1995, Hardesty et al. 1997). Although each state (except those for Longleaf Pine) is associated with very low habitat suitability value of 1, it was important to include these low suitability states because RCW habitat could be converted to these other states through long-term successional processes or through immediate human modification to the landscape, which could have important consequences for RCW populations.

Longleaf pine states

The remaining 30 states in the ST-SIM model belong to the broad Longleaf Pine landcover class and represent RCW habitat at various levels of suitability (Table 2; Figure 7). We separated the Longleaf Pine landcover class into several states, given both the observed specificity in RCW foraging habitat selection and the wide range of longleaf pine stand conditions found throughout Eglin AFB. Generally, preferred habitat for RCWs consists of mature, open longleaf pine savannas with large/old trees, sparse midstory, and lush herbaceous groundcover (Hardesty et al. 1997, James et al. 2001, Walters et al. 2002, USFWS 2003). Studies have shown that RCW stand-use declines as the density of small pines (Porter and Labisky 1986, Walters et al. 2000, Walters et al. 2002) and the density (Hooper and Harlow 1986, Jones and Hunt 1996) and height (Walters et al. 2000, Walters et al. 2002) of trees in the midstory increase. In addition, larger, more productive RCW groups are found in areas with a high percentage cover of grasses and forbs in the understory (James et al. 1997). Therefore, the Longleaf Pine states used within the ST-SIM model were characterized by age, overstory BA, midstory suitability, and herbaceous groundcover (Table 2).

Table 2. Thresholds for Longleaf Pine states that describe canopy BA, midstory density and height, and understory groundcover, relevant to RCW habitat suitability, used in the ST-SIM landscape model of longleaf pine ecosystem dynamics at Eglin AFB.

Category	Threshold Value	References and Support
Canopy BA (i.e., trees ≥ 25 cm DBH)		
High BA Moderate / Suitable BA Low BA	> 15.75 m^2/ha (70 ft^2/ac) 2.25 – 15.75 m^2/ha (10 – 70 ft^2/ac) < 2.25 m^2/ha (10 ft^2/ac)	Observed average BA for stands preferred by RCWs was 16.1 m^2/ha (70 ft^2/ac ; Porter and Labisky 1986). 2003 recovery criteria require a BA of at least 9.2 m^2/ha for trees ≥25 cm DBH (40 ft^2/ac; USFWS 2003). Stands avoided by RCWs had BAs > 17.0 m^2/ha (74 ft^2/ac; Porter and Labisky 1986). Densities of stands used by RCWs reported north of Florida range from 9.2 – 13.8 m^2/ha (40 – 60 ft^2/ac; reviewed in Hopkins & Lynn 1971; USFWS 2003). Median BA for stands with RCWs in FL panhandle was 10.6 m^2/ha (46 ft^2/ac; Hovis and Labisky 1985).
Midstory Suitability		
High Suitability Moderate Suitability Low Suitability	BA < 100 m^2/ha Height ≤ 2 m and BA 100 – 200 m^2/ha Height > 2 m and BA > 200 m^2/ha	Median midstory height for stands with RCWs in FL panhandle was 1.6 m (Hovis and Labisky 1985). 2003 recovery criteria require that midstory height be less than 2.1 m (USFWS 2003). Loeb et al. (1992) found a significant difference between the midstory BA of stands with active RCW clusters (average BA = 135 m^2/ha) and those with inactive clusters (average BA = 244 m^2/ha).
Understory Cover (i.e., % cover by native grasses and other herbs)		
High Cover Low Cover	≥ 40% < 40%	James et al. (2001) found that health of RCW populations was related to groundcover composition and recommend that wiregrass or other herbaceous groundcover constitutes at least 40% of the total groundcover. Also listed as a requirement in recovery criteria (USFWS 2003).

Longleaf pine states were first broken into three age classes based on studies of RCW foraging habits: (*i*) Young Pine (0-14 years), (*ii*) Longleaf Pine 15-59 years old, and (*iii*) Longleaf Pine ≥ 60 years old. Multiple studies have shown that RCWs select large, old trees over small, young trees for foraging (Hooper and Lennartz 1981, Porter and Labisky 1986, DeLotelle et al. 1987, Bradshaw 1995, Jones and Hunt 1996, Engstrom and Sanders 1997, Hardesty et al. 1997, Zwicker and Walters 1999, Walters et al. 2000, Walters et al. 2002), preferring stands with trees that are 60 years or older. Furthermore, RCW productivity and fitness are positively affected by the availability of stands containing trees of advanced ages (Zwicker and Walters 1999, Walters et al. 2000, Walters et al. 2002). Therefore, we associated the highest levels of RCW habitat suitability with all states contained within the Longleaf Pine ≥ 60 years category and lower habitat suitability for all states within the Longleaf Pine 15-59 years category (Figure 7). The Young Pine state was given the lowest level of suitability (1). Because tree age consistently correlates with RCW habitat suitability and other habitat characteristics throughout the species' range, the basic premises of the landscape model are transferable to other sites.

In addition, RCWs preferentially forage in longleaf pine stands or patches within those stands that have lower (but not open) canopy BAs (Bowman et al. 1997, Doster and James 1998, Walters et al. 2000, Walters et al. 2002). To capture this difference in habitat preference/suitability, we also included three levels of canopy BA for the Longleaf Pine 15-59 years and the Longleaf Pine ≥ 60 years classes (Table 2; Figure 7), ranging from High to Suitable to Low Canopy BA. The canopy BA thresholds detailed in Table 2 are supported by work by Hardesty et al. (1997) that showed that RCWs at Eglin AFB used and had high reproductive success in stands with lower pine BAs meeting these thresholds. Within the ST-SIM model, states characterized by Suitable Canopy BA had higher levels of RCW habitat suitability, followed by those characterized by High and then Low Canopy BA (Figure 7).

Finally, we included five states within each of the three levels of canopy BA for the Longleaf Pine 15-59 and Longleaf Pine ≥ 60 age classes that describe midstory and understory characteristics. In these states, midstory suitability is characterized by a combination of height and density, and these categories range from High to Moderate to Low Suitability (Table 2; Figure 7). A wide range of studies have shown that RCW patch- and stand-use as well as RCW reproductive success and fitness decline with increasing midstory height and density (e.g., Hooper and Harlow 1986, Bradshaw 1995, Hardesty et al. 1997, Doster and James 1998, Walters et al. 2000, Walters et al. 2002).

Similarly, because RCW fitness and stand-use decline with decreasing groundcover by native herbs (Hardesty et al. 1997, James et al. 1997, James et al. 2001), we describe the understory as having either a High Cover of herbaceous plants (≥ 40% of total groundcover) or a Low Cover (< 40% of total ground cover; Table 2; Figure 7). The 40% threshold considers the absolute percentage of ground covered by herbaceous plants. This threshold was previously advocated by James et al. (2001) and incorporated as a required foraging habitat condition in the recovery criteria for the species (USFWS 2003). Within the ST-SIM model, the highest levels of habitat suitability are associated with states that have a combination of High Midstory Suitability and High Cover (suitability = 5), and suitability declines to the lowest level (suitability = 1) when the state is characterized by Low Midstory Suitability and Low Cover.

Landscape transitions

In any ST-SIM model, landscape cells within the model move from one landscape state to another through probabilistic or deterministic transitions. In our baseline landscape model of the

longleaf pine ecosystem, those transitions occur for each 1-acre landscape cell through (1) natural processes (e.g., succession, aging, or natural wildfires) and (2) management (e.g., prescribed burns, herbicide treatments, or mechanical midstory removal).

Succession and aging

Longleaf pine ecosystems transform from savanna-like woodlands to closed canopy forests with higher overstory density and lower understory species richness and abundance when fire is suppressed (Ware et al. 1993, Brockway and Lewis 1997, Gilliam and Platt 1999, Rodgers and Provencher 1999, Provencher et al. 2001a, Glitzenstein et al. 2003). Without fire, longleaf ecosystems ultimately develop into forests of mixed pine and xeric/mesic hardwoods (Veno 1976, Myers 1985) that are unsuitable for RCWs (Hooper and Lennartz 1981, Repasky 1984, Porter and Labisky 1986, Bradshaw 1995, Hardesty et al. 1997). However, variations in soil type, moisture, and fertility can change how specific longleaf pine ecosystems (e.g., spodosol vs. ultisol flatwoods) respond to similar fire frequencies based on differences in ecosystem productivity (Mitchell et al. 1999, Glitzenstein et al. 2003). For example, a moister, more fertile site, where the hardwood midstory grows at a faster rate, may require more frequent fires to disrupt successional dynamics compared to a drier, less fertile site.

At Eglin AFB, the predominant soil type is Lakeland Sand, which is the driest and least fertile type in Florida (reviewed in Henderson 2006). Here, the predicted fire return interval was historically ≤ 6 years (Henderson 2006). The results of this study and previous models also show that fire return intervals of < 5 years are needed to ensure the maintenance of high-quality conditions for RCWs and other species (this report; Hiers et al. 2003). In the ST-SIM landscape model for Eglin AFB, we assumed that it would take 5-, 15-, or 20-year increments of fire suppression to alter midstory and understory conditions enough to warrant a change in successional state but that canopy BA would not change over such short time scales (Figure 7). Thus, for example, a stand that has a Suitable Canopy BA, High Midstory Suitability, and High Cover would move to the next successional state (Suitable Canopy BA, Moderate Midstory Suitability, and High Cover) if fire did not occur in that stand within 15 years. If another 5 years progress without fire, the stand would move from that new state to the state characterized by Suitable Canopy BA, Moderate Midstory Suitability, and Low Cover as the growing midstory begins to outcompete the herbaceous groundcover (and so on; Figure 7). We also included a successional transition from the oldest longleaf pine state with High Canopy BA, Low Midstory Suitability, and Low Cover to the Mixed state to account for the fact that a longleaf pine stand would begin to contain a relatively even density of hardwoods and pine trees after many years of fire suppression (e.g., >> 40 years; Veno 1976).

In addition, we included a transition for aging in longleaf pine stands within ST-SIM simulations because tree age is relevant to RCW habitat suitability. During a simulation, the longleaf pines within landscape cells will age by one year with each model time step. If the age of pines progresses from 14 to 15 years, the cell's state will move from the Young Pine state to the state characterized by Longleaf Pine 15-59 years, High Canopy BA, Moderate Midstory Suitability, and High Cover (reflective of the successional pathway for plantation pine stands; Figure 7). Likewise, if a stand's age progresses from 59 to 60 years for a longleaf pine state during the course of a simulation, then the cell will move from the successional state within the Longleaf Pine 15-59 years class to the corresponding successional state within the Longleaf Pine ≥ 60 years class (Figure 7). If both an age and a successional threshold are crossed in the same time step (e.g., a cell in the Longleaf Pine 15-59 class that is 59 years old and has not

experienced a fire for 14 years), then the cell's state would both age up to the Longleaf Pine ≥ 60 class and advance forward one step in the corresponding successional pathway in the next time step (Figure 7). Because forest structure and age are irrelevant for all non-longleaf pine states, we did not include transitions for succession and aging for the Developed, Mixed, Hardwood, Water, Sand Pine, or Bare Land states.

Fire

The longleaf pine ecosystem is highly adapted to and dependent on fire. Longleaf pines produce large seeds with persistent wings, requiring frequent fires to clear ground-level leaf litter so that seeds can penetrate into the soil. After germination, a seedling will spend an extended period in the grass-stage, where a terminal bud is protected by a tuft of needles and a large taproot is developed. Following this period, saplings grow rapidly to a height that is safe from low-intensity fires, and adult longleaf pines begin to produce thick, fire-resistant bark (reviewed in Henderson 2006). In addition, longleaf pines produce resinous, highly flammable needles that promote frequent surface fires (Mutch 1970) while wiregrass, an herbaceous understory plant found in 90% of longleaf systems, is also highly flammable but able to survive fire (Early 2004). Therefore, this community promotes a self-reinforcing fire regime that favors longleaf pines and associated species and excludes less fire-tolerant species (e.g., many hardwood species; Platt et al. 1988). In addition, studies examining restoration techniques in longleaf pine ecosystems have shown that prescribed burns decreased oaks in smaller size classes by 20% compared to controls (Provencher et al. 2001b), increased understory densities (Provencher et al. 2001a, Provencher et al. 2001b), and created plant, arthropod, herpetofauna, and bird communities that were more similar to frequently burned reference plots (Provencher et al. 2001c, Provencher et al. 2002a, Provencher et al. 2002b, Provencher et al. 2002c).

When fire occurs frequently, ground litter is burned regularly, and fires occur at relatively low intensities that are beneficial to the longleaf community. However, because the severity of fire depends on the rate of spread and weight of fuel consumed (Oliver and Larson 1990), fires become more intense after prolonged periods of fire suppression and litter accumulation (Christensen 1981). Previous case studies have shown that, when fire is restored to areas with prolonged histories of fire suppression, longleaf pine stands can experience 75-100% mortality in larger tree classes (Varner et al. 2005). Given this information, we assumed that fires would occur at high or low intensities depending on the preceding period of fire suppression as reflected in the current state of the stand (Figure 8; Figure 9). Low intensity fires, which occur in states that have been burned within 35 years, do not impact the canopy BA but do shift the stand one state to the left in the successional sequence (Figure 8; Figure 9). High intensity fires occur in states that have not been burned in more than 35 years and impact canopy BA, midstory suitability, and herbaceous groundcover by moving the state one level below and two states to the left in the successional sequence (Figure 8; Figure 9).

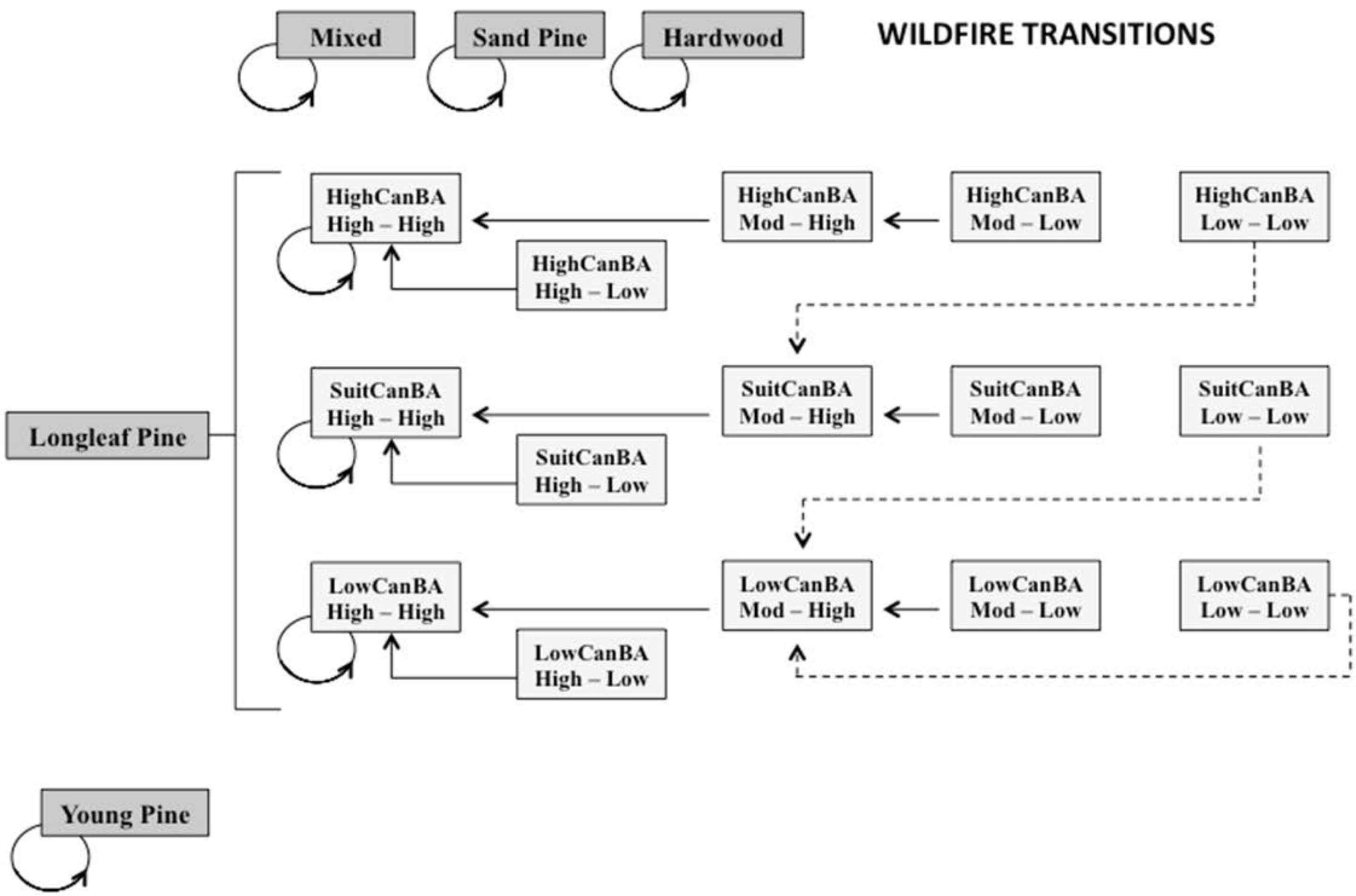


Figure 8. Transition pathways for landcover states as a result of wildfires in the ST-SIM landscape model for Eglin AFB. Transitions for low intensity fires, which occur in states that have recently been burned and contain a thin layer of ground litter, are shown in solid lines. Transitions for high intensity fires, which occur in states with a history of fire suppression and contain a thick layer of ground litter, are shown in dashed lines. Transitions for longleaf pine states are the same for the ≥ 60 years old and 15-59 years old age classes. Finally, 1-acre landscape cells within all forested landcover states have an equal probability of experiencing a wildfire each year (2.2%).

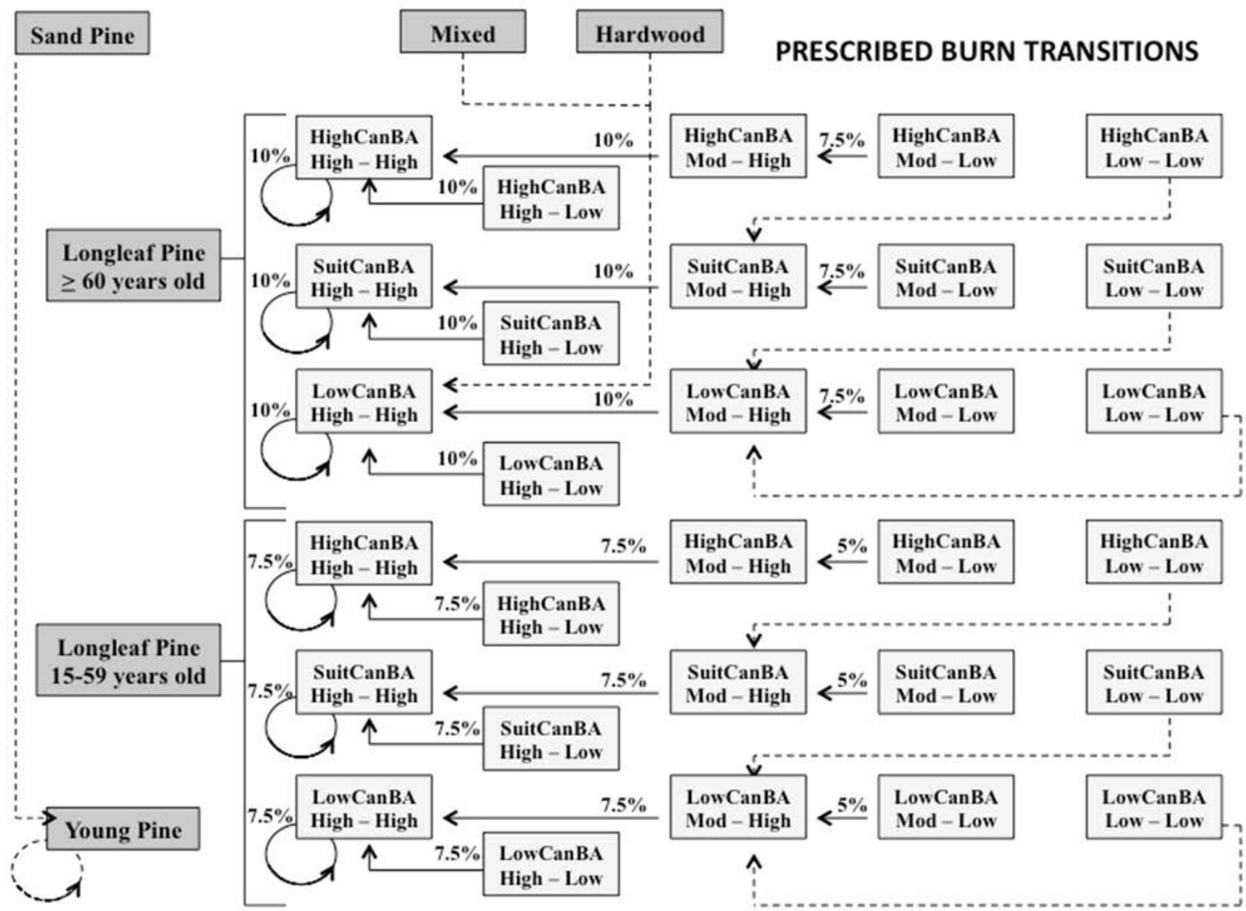


Figure 9. Transition pathways for states as a result of prescribed burns in the ST-SIM landscape model for Eglin AFB. Probabilities given next to transition lines indicate the likelihood that landscape cells belonging to each state will experience a prescribed burn in a given time step relative to the other states. State transition pathways illustrated by dashed lines have a 0% probability of occurring in the baseline model. These landcover types are rarely burned on the actual Eglin landscape, and pathways were provided only to allow the user to test alternative management regimes.

In the ST-SIM model, as in the actual landscape at Eglin AFB, fires either occur as wildfires (i.e., occurring through lightning strikes, arson, or other means) or as intentional prescribed burns set for management purposes. We parameterized the model such that both wildfires (Figure 8) and prescribed burns (Figure 9) impact landscape cells belonging to the Longleaf Pine states in the same manner, namely by increasing habitat suitability for RCWs. However, we varied other simulation rules between the two fire types. First, landscape cells within all forest landcover states (i.e., Hardwood, Mixed, Sand Pine, Young Pine, and Longleaf Pine) have an equal probability (2.2%) of experiencing a wildfire each simulation year. This probability corresponds to approximately 10,000 acres of the simulation landscape being burned by wildfires annually, comparable to the actual Eglin AFB landscape (Eglin AFB Fire Management Data; Hiers, pers. . 2010). Furthermore, we assumed that a single wildfire would not have a major impact on landscape cells belonging to the Hardwood, Sand Pine, Mixed, or

Young Pine states, and cells within these states retain their original state following a wildfire. Cells characterized by Longleaf Pine (either within the 15-59 years or ≥ 60 years age classes), however, shift along their successional pathways as shown in Figure 8.

In contrast, we parameterized the model such that the impact and probability of prescribed burning varied by landcover state. Instead of being modeled as a strict probability of occurring, we simulated an annual management target of 104,000 acres (Table 3) for Eglin AFB - the actual target for the installation as of 2014 (Eglin AFB Fire Management Data; Hiers, pers. comm. 2014). Landcover states that could experience a prescribed burn were then given a probability of occurrence. However, unlike the probabilities given for the wildfire transition, these probabilities instead provide a relative ranking by which cells in each landcover state experience prescribed burns (Figure 9). For example, cells characterized by higher quality longleaf pine states (i.e., ≥ 60 years old with High Midstory Suitability and High Cover) have a greater probability of being burned (10%) compared to those characterized by similar quality but younger (i.e., 15-59 years) longleaf pine states (7.5%). With this parameterization, the ST-SIM model will always simulate a prescribed burn in enough cells to meet the annual management target of 104,000 acres (as long as cells within eligible states are present); however, cells belonging to states with the highest "probability" of being burned will experience the transition first, followed by those within the state with the next highest probability, and so on until the management target has been met. These probabilities were selected based on actual burn patterns at Eglin AFB (Eglin AFB Fire Management Data; Hiers, pers. comm. 2014).

Table 3. Management types and their area targets included in the baseline ST-SIM model of the longleaf pine ecosystem on Eglin AFB (Hiers, pers. comm. 2014). A user can alter these targets, and other parameters, to explore the impacts of alternative management regimes.

Transition Type	**Annual Management Target (acres)**
Prescribed burn	104,000
Herbicide	1,000
Mechanical midstory removal	7,000

In addition, we included pathways for prescribed burns for cells within the Young Pine and non-longleaf pine states (Figure 9). However, we parameterized the baseline landscape model such that cells within these states had a 0% relative probability of experiencing a prescribed burn, given that only very small areas of these types of forest stands are burned each year (Eglin AFB Fire Management Data; Hiers, pers. comm. 2014). These pathways were provided so that the user could explore the impacts of alternative burning regimes on the base by increasing the probability from 0% for each state (for instructions, see Appendix D).

Finally, we varied the size of both wildfires and prescribed burns in the model according to actual fire behavior at Eglin AFB. In the model, as on the real landscape, a single wildfire or prescribed burn can consume from < 5 contiguous acres to more than 4,000 contiguous acres at a time. Most individual (i.e., contiguous) wildfires are smaller and impact < 5 acres (mean: 95 acres, median: 5 acres, St.D: 355), and most individual prescribed burns impact between 50 and 2000 acres (mean: 709 acres, median: 415 acres, St.D: 815; Figure 10; Eglin AFB Fire Management Data). The size of every fire simulated for each model time step was chosen based on the distribution of size classes shown in Figure 10.

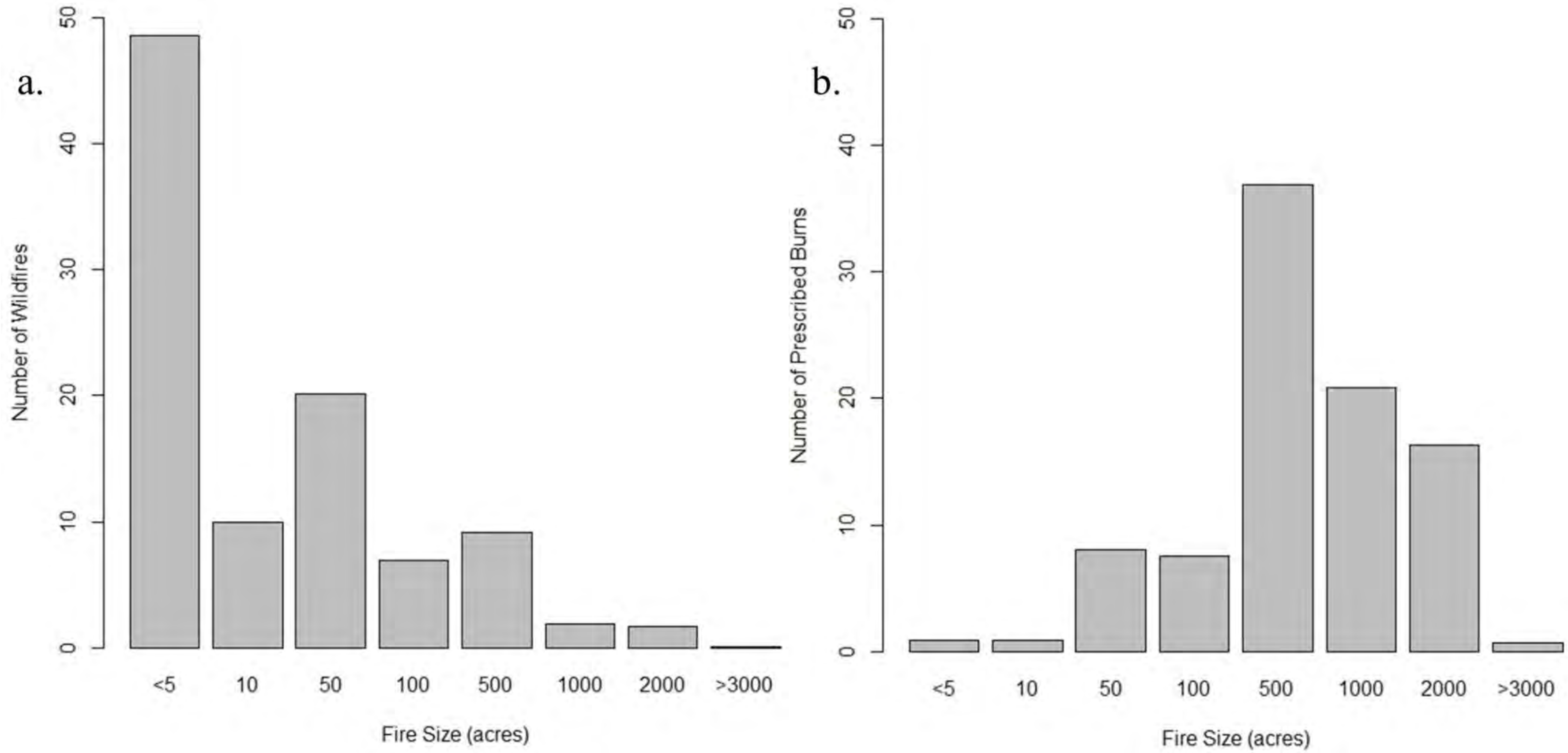
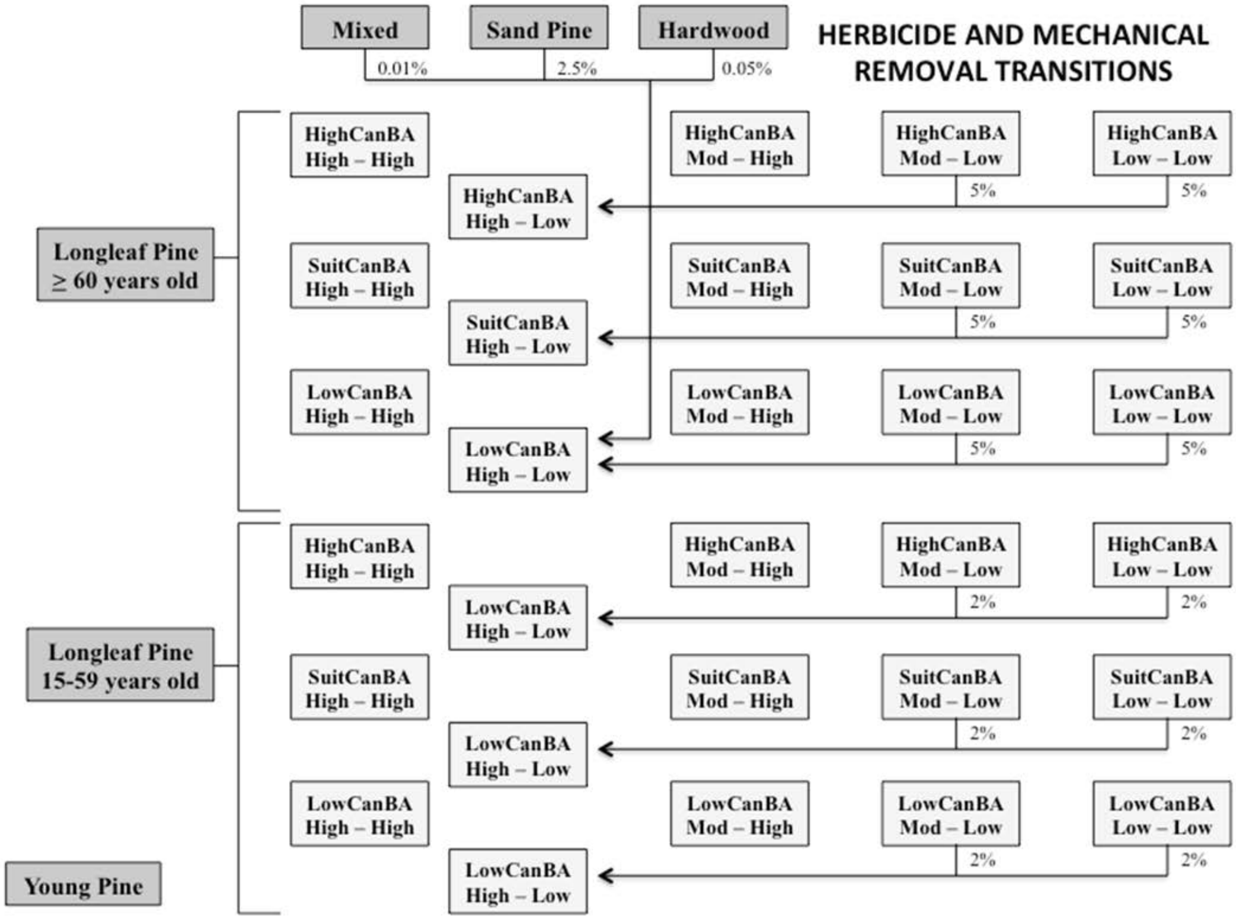


Figure 10. Average annual frequency of fires in each size class for (a) wildfires and (b) prescribed burns at Eglin AFB (data from Eglin AFB Fire Management from 1998-2011). X-axis intervals encompass the range from the previous interval to the current interval (e.g., "10" on x-axis shows the number of fires from 6 to 10 acres in size, "50" shows the number of fires from 11 to 50 acres in size, etc).

Herbicide and mechanical removal

In addition to fire, a large-scale study of restoration techniques at Eglin AFB also showed that the use of herbicides and the mechanical chainsaw felling and girdling of hardwood species in the midstory (hereafter, "mechanical midstory removal") were extremely effective in reducing the hardwood midstory. Oaks in the smallest size classes decreased by 60% and 90% following herbicide and mechanical removal treatments, respectively, compared to control plots (Provencher et al. 2001a, Provencher et al. 2001c). Irrespective of the method, this reduction in hardwood tree density followed by a spring burn ultimately resulted in a higher presence of RCWs and other bird species associated with longleaf pine ecosystems compared to control plots (Provencher et al. 2002b, Provencher et al. 2002c). However, although herbicide and mechanical removal improved midstory suitability, these management techniques alone did not improve the condition of the herbaceous understory compared to control and fire plots (Provencher et al. 2001a).

Given the effectiveness and widespread use of herbicide and mechanical removal in restoring longleaf pine communities, we included these management techniques as potential management options in the ST-SIM landscape model. We parameterized the model such that herbicide application and mechanical midstory removal do not impact canopy BA or improve understory condition but do improve RCW habitat suitability by increasing midstory suitability (Figure 11). In addition, as with prescribed burning, we modeled these transition types as management targets (Table 3) that could occur only in landscape cells characterized by certain landcover states (Figure 11). Finally, herbicide and mechanical removal treatments could occur in the landscape in 200 to 500 acre blocks of contiguous 1-acre landscape cells. These parameters are comparable to management targets and application patterns currently used throughout Eglin AFB (Hiers, pers. comm. 2014).



[1]Landscape cells in the Sand Pine state have a 0% probability of experiencing an herbicide transition but a 2.5% probability of experiencing a mechanical removal transition.

Figure 11. Transition pathways for landcover states following herbicide and mechanical removal treatments in the ST-SIM baseline landscape model for Eglin AFB. Probabilities given next to transition lines indicate the likelihood that landscape cells belonging to each state will experience a management treatment in a given time step relative to the other states (probabilities equivalent for herbicide and mechanical midstory removal[1]).

Other transitions

In the baseline model, we did not include other important transitions, such as ongoing infrastructure development on the base or encroachment of invasive sand pine. Instead, we elected to allow the user to simulate the impacts of these threats at differing rates (e.g., see Section 3.5). This is important to note, however, because this assumption could automatically reduce the accuracy of ST-SIM model predictions – particularly because development likely increased the area of the Developed state and decreased the area of other forested states between 2001 and 2010 (the timeframe of model validation; see Section 4.3).

3.3.3 Validation of the Baseline Model

As in the RCW population model described in the previous section, it was important that we validated our ST-SIM baseline landscape model to ensure that it offered a robust

representation of the longleaf pine ecosystem dynamics at Eglin AFB. To accomplish this, we conducted a non-spatially explicit as well as a spatially explicit comparison between predictive landcover maps generated by the ST-SIM baseline simulation and reference landcover maps classified from remotely sensed imagery.

Reference landcover

In order to validate our model, we created reference datasets that illustrated the actual amount and distribution of landcover states throughout the base for the years 2001, 2003, 2007, and 2010 (see Appendix E1 for details on how these reference maps were created). These reference datasets were based largely on GIS landcover datasets produced from remotely sensed imagery by the staff at Eglin AFB. After modification and processing, the resulting reference landcover state maps (resolution: 1 acre) showed the actual area and distribution of the landcover states recognized by the ST-SIM model. The areas of the broad landscape state classes for the reference maps are shown in Table 4 and Figure 12.

Table 4. The observed areas of the Eglin AFB landscape in each state class according to reference GIS landcover maps of the base for the years 2001, 2003, 2007, and 2010 compared to the average areas predicted by the ST-SIM baseline simulation.

Year	State Class	Observed Area (acres)	Average[1] Predicted Area (acres)	Standard Deviation[1] in Predicted Area	Percentage Error (%) (Observed:Predicted)
2001					
	Young Longleaf	21,479	21,437	205.56	-0.20
	Old Longleaf[2]	132,656	132,222	276.94	-0.33
	Sand Pine	81,209	80,986	289.22	-0.27
	Mixed	118,521	118,392	262.16	-0.11
	Hardwood	51,517	51,467	297.74	-0.10
	Developed	7,333	7,311	68.27	-0.30
	Bare Land	49,318	49,254	180.55	-0.13
	Water	1,743	1,745	32.18	0.10
2003					
	Young Longleaf	20,439	18,615	177.66	-8.92
	Old Longleaf[2]	132,704	145,103	280.25	9.34
	Sand Pine	79,956	71,212	295.45	-10.94
	Mixed	116,666	118,298	266.08	1.40
	Hardwood	51,535	51,274	299.29	-0.51
	Developed	6,272	7,311	68.27	16.56
	Bare Land	54,390	49,254	180.55	-9.44
	Water	1,812	1,745	32.18	-3.70
2007					
	Young Longleaf	14,884	13,378	129.56	-10.12
	Old Longleaf[2]	126,148	173,333	316.62	37.40
	Sand Pine	75,877	49,140	395.32	-35.24
	Mixed	123,348	118,000	269.47	-4.34
	Hardwood	51,577	50,653	277.42	-1.79
	Developed	5,247	7,311	68.27	39.34
	Bare Land	64,848	49,254	180.55	-24.05
	Water	1,845	1,745	32.18	-5.45
2010					
	Young Longleaf	12,540	9,718	121.11	-22.50
	Old Longleaf[2]	129,046	196,471	331.97	52.25
	Sand Pine	73,756	31,034	394.28	-57.92
	Mixed	122,649	117,559	262.50	-4.15
	Hardwood	51,602	49,721	268.40	-3.65
	Developed	5,632	7,311	68.27	29.80
	Bare Land	66,699	49,254	180.55	-26.16
	Water	1,849	1,745	32.18	-5.65

[1]Values reflect the average area and standard deviation for each state class across 10 iterations of the ST-SIM baseline simulation.

[2]All longleaf pine states for the broader "Longleaf Pine 15-59" and "Longleaf Pine ≥ 60" state classes were grouped together for this analysis.

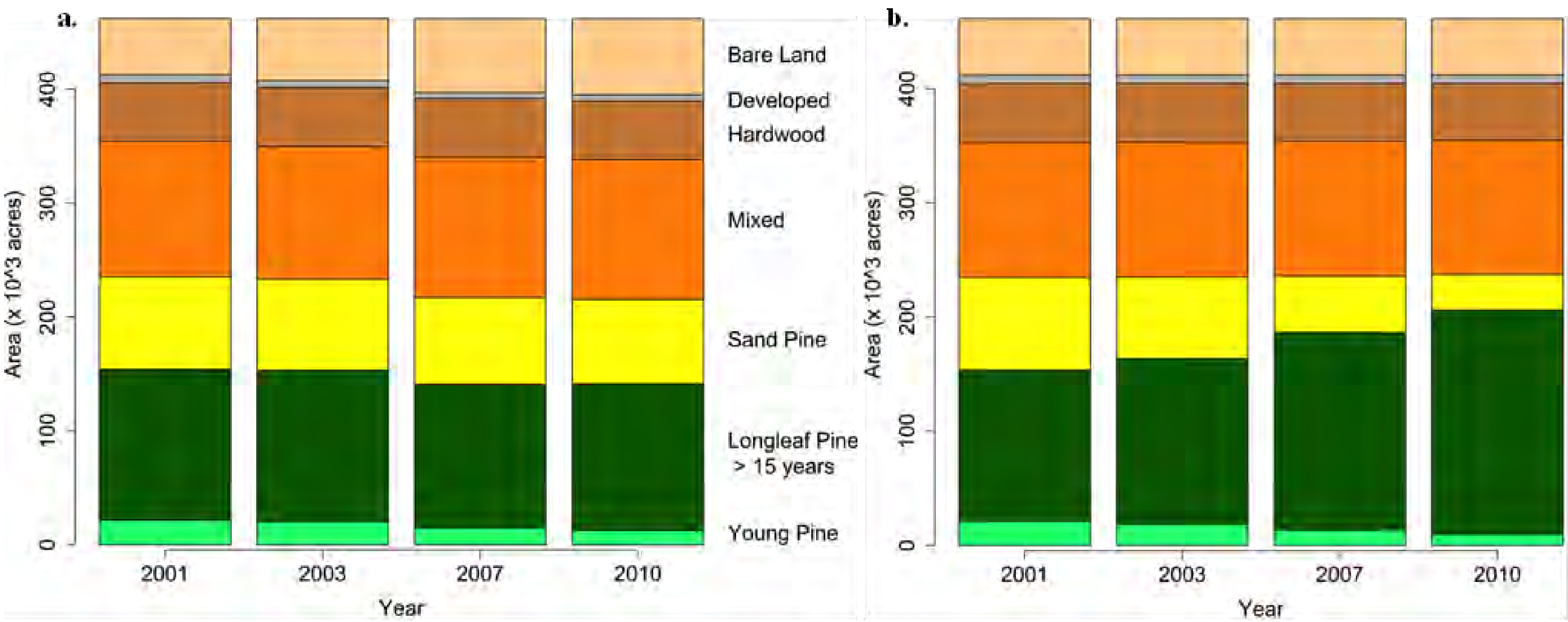


Figure 12. Areas of broad landcover states for (a) reference maps (based on satellite imagery) for the years 2001, 2003, 2007, and 2010 and (b) maps as predicted by the ST-SIM baseline model.

Predicted Landcover

We then generated predictive landcover state maps for Eglin AFB using the ST-SIM landscape model. We parameterized the model using the baseline states, transitions, and management target values described in the previous sub-section. We initialized the model using the 2001 reference landcover state map, where the amount and distribution of the landcover states at time step 0 matched those observed through satellite imagery in 2001. The staff at Eglin AFB collected ground-truthing landcover points in 2001 in order to assess the accuracy of the landcover classification used to create this map from satellite imagery. Through this analysis, the staff found that the map had an accuracy of 81% (Laine, unpublished data.). It is important to note, therefore, that any errors present in an initialization map will be propagated throughout the ST-SIM simulation and influence the accuracy of any future predictive maps.

We ran the model for 10 time steps, where 1 time step = 1 year. In addition, the ST-SIM platform is a stochastic model; in this example, fire and management actions occur throughout the base according to user-specified probabilities, and the locations of these disturbances could vary each time the model is simulated. Therefore, we ran 10 iterations of the model, producing 10 independent versions of the 10-year model. At simulation completion, we exported an Excel table showing the area of the landscape in each state class for every year and iteration as well as a map of the landcover states for the year 2010 (model time step 9). These outputs were compared to the reference landcover state areas and maps for validation.

Non-spatially explicit validation

We conducted a non-spatially explicit validation to determine if the model could accurately predict the proportion of the landscape that fell into each landcover state throughout the entire base. In the non-spatially explicit analysis, we only considered the model's predictions for the area covered by each landscape state. If the area for a given state on the real landscape was statically equivalent to the area predicted by the model, we said that this result validated the moded (repeated for each state). Because we were only concerned with broad areas (and not the exact location of given predictions), we refer to this as non-spatially explicit. Using the reference landcover state maps, we calculated the area covered by each state class, creating a distribution for these areas for each available year (2001, 2003, 2007, 2010). We calculated equivalent distributions for the average areas of the state classes across the 10 iterations predicted by the ST-SIM baseline simulation for the same years. For ease of analysis, we grouped states into the broad landcover classes: Mixed, Hardwood, Sand Pine, Young Pine, Longleaf Pine, Bare Land, Developed, and Water.

For each year, we then compared the actual landcover state distribution to the predicted average distribution using a chi-square test of homogeneity. This test is generally applied to a frequency count for a single categorical variable (i.e., the area of each landcover state type) from two different populations (i.e., the reference and predicted landscapes). We rejected the null hypothesis (i.e., that the area distributions for the reference and predicted landcover states were the same) at a significance level $p < 0.01$. All data analyses were performed in R (R Development Core Team 2014). This validation allowed us to evaluate whether the model could accurately predict the availability of landcover types, most importantly, the area of suitable RCW habitat.

Finally, we used the same statistical procedure to compare the 2010 predicted landcover distributions for stochastic iterations 2 through 10 to iteration 1. This analysis allowed us to evaluate whether or not different iterations, operating under the same parameters and initial conditions, produced significantly different results.

Spatially explicit validation

We also conducted a spatially explicit validation to determine if, in addition to predicting landcover availability correctly, the model could also accurately predict the locations of the various landcover states. In this case, we looked at specific geographic coordinates to determine if the model's predicted landscape state at that location matched that of the real landscape. Because we were concerned with both the state prediction and the location of that prediction, we refer to this as a spatially explicit analysis. To do this, we followed the protocol recommended by the US National Park Service (Lea and Curtis 2010).

In ArcGIS, we created a vector layer with 9,946 points that were randomly distributed throughout the base using the "Create Random Points" tool in ArcToolBox. We determined the reference and predicted landcover states associated with each point on the respective 2010 landcover maps (repeated 10 times for the 10 model iterations). We then created a contingency table for each model iteration (10 tables total), each showing the proportion of random points (p_{ij}) that was characterized by column j (reference landcover) and row i (predicted landcover). In each table, the values along the diagonal indicated the proportion of points that were classified correctly on the predicted landcover state maps. In each contingency table, we calculated accuracy as:

$$\text{Overall Accuracy} = \frac{(\sum^{i=landcover\ state\ classes} p_{iI})}{p_{++}},$$

where overall accuracy is the sum of all proportions along the diagonal of the contingency table (p_{iI}) divided by the sum of all row totals (p_{++}; here, 1). We also determined the amount of chance agreement between the reference and predicted maps according to the following equation:

$$\text{Chance Agreement} = \sum_{i=J}^{landcover\ state\ classes} p_{i+} * p_{+J},$$

where chance agreement is the sum of the product of the corresponding row (p_{i+}) and column (p_{+J}) totals. Finally, we calculated Cohen's kappa (or the kappa coefficient), which scales from 0 under random mapping to 1 under perfect accuracy:

$$Kappa = \frac{Overall\ accuracy - chance\ agreement}{1 - chance\ agreement}.$$

This coefficient was previously recommended as the optimal standardized statistic for assessing thematic accuracy because it incorporates chance agreement between classes (reviewed in Foody 2002).

3.4 The RCW DSS

3.4.1 Background and objectives

In dynamic, disturbance-dependent landscapes like the longleaf pine ecosystem at Eglin AFB, habitat amount, connectivity, and quality vary spatiotemporally with the frequency and intensity of environmental disturbances. In such environments, habitat quality, as viewed from the perspectives of disturbance-reliant species like RCWs, declines over successional time but can be improved quickly following new disturbances (e.g., Stelter et al. 1997, Conner et al. 2001, Catlin et al. 2013). As a result, metapopulations in dynamic environments tend to have a higher risk of extinction (Stelter et al. 1997, Keymer et al. 2000) and lower occupancy levels (Hanski

1999, Johnson 2000, Keymer et al. 2000, Amarasekare and Possingham 2001, Johst et al. 2002, Cornell and Ovaskainen 2008, Hodgson et al. 2009) compared to those in more stable environments (Hanski 1999, Johnson 2000, Keymer et al. 2000, Amarasekare and Possingham 2001, Johst et al. 2002, Cornell and Ovaskainen 2008).

Key elements of a species' life history evolution and habitat needs are also widely predicted to differ for species in dynamic versus static environments (e.g., Hanski 1999, Keymer et al. 2000, Wimberly 2006, Johst et al. 2011). As a result, landscape dynamism can be a "game-changer" for resident species, and management strategies developed for species in more static environments may not be applicable. For example, simulations predict that at least 50% more habitat (Kerezsy et al. 2013) and higher levels of connectivity are required for species inhabiting dynamic landscapes compared to those in stable landscapes (DeAngelis et al. 2010) because of the constant destruction of habitat and the time lags between new habitat creation and colonization (Zozaya et al. 2012). Maintaining even small habitat patches is also arguably more important for metapopulation persistence in dynamic landscapes because they can act as refugia during disturbance events (Brown and Kodric-Brown 1977). As a consequence, understanding underlying landscape processes is critical for appropriately managing species in dynamic environments.

Furthermore, aspects of the most prevalent threats to species persistence are mediated through the landscape, including habitat loss and fragmentation, pollution, alteration of habitat dynamics, and climate change (Wilcove et al. 1998, Lawler et al. 2002). Therefore, to accurately predict population trends and extinction risk, both the landscape and the focal species' life history should be considered. To this point, studies have shown that both landscape elements and population dynamics must be considered for species in disturbance-dependent ecosystems because failing to do so can result in overly optimistic predictions of population viability (Akçakaya et al. 2004, Fordham et al. 2014).

Thus, one of the primary objectives of this Research Project was to link the ST-SIM landscape model described in Section 3.3 with the RCW population model described in Section 3.2. This coupled model, the RCW DSS, was designed as a tool for use by base natural resource managers to assess the impacts of management applications, development projects, and threats on RCW populations. In this section, we describe modifications made to the RCW population model version 2.0 (described in Section 3.2) to create version 3.0 for use within the RCW DSS as well as the results of baseline scenarios and validation exercises for the paired-model system.

3.4.2 Overview of the RCW DSS

The RCW DSS was developed as two independent but connected models (Figure 13) under the "metamodel approach", conceptualized as the linking of often discipline-specific models representing components of a larger system in order to reveal emergent properties of multi-dimensional interactions (Lacy et al. 2013). In the RCW DSS, the ST-SIM landscape model is simulated for a user-specified number of times steps, and the spatially explicit results of this model can be exported in temporal increments of the user's choosing (e.g., we recommend producing maps every 5-10 years). These predictive maps can then be uploaded into the RCW population model version 3.0 as input files, allowing the user to evaluate RCW population dynamics as habitat suitability changes through time.

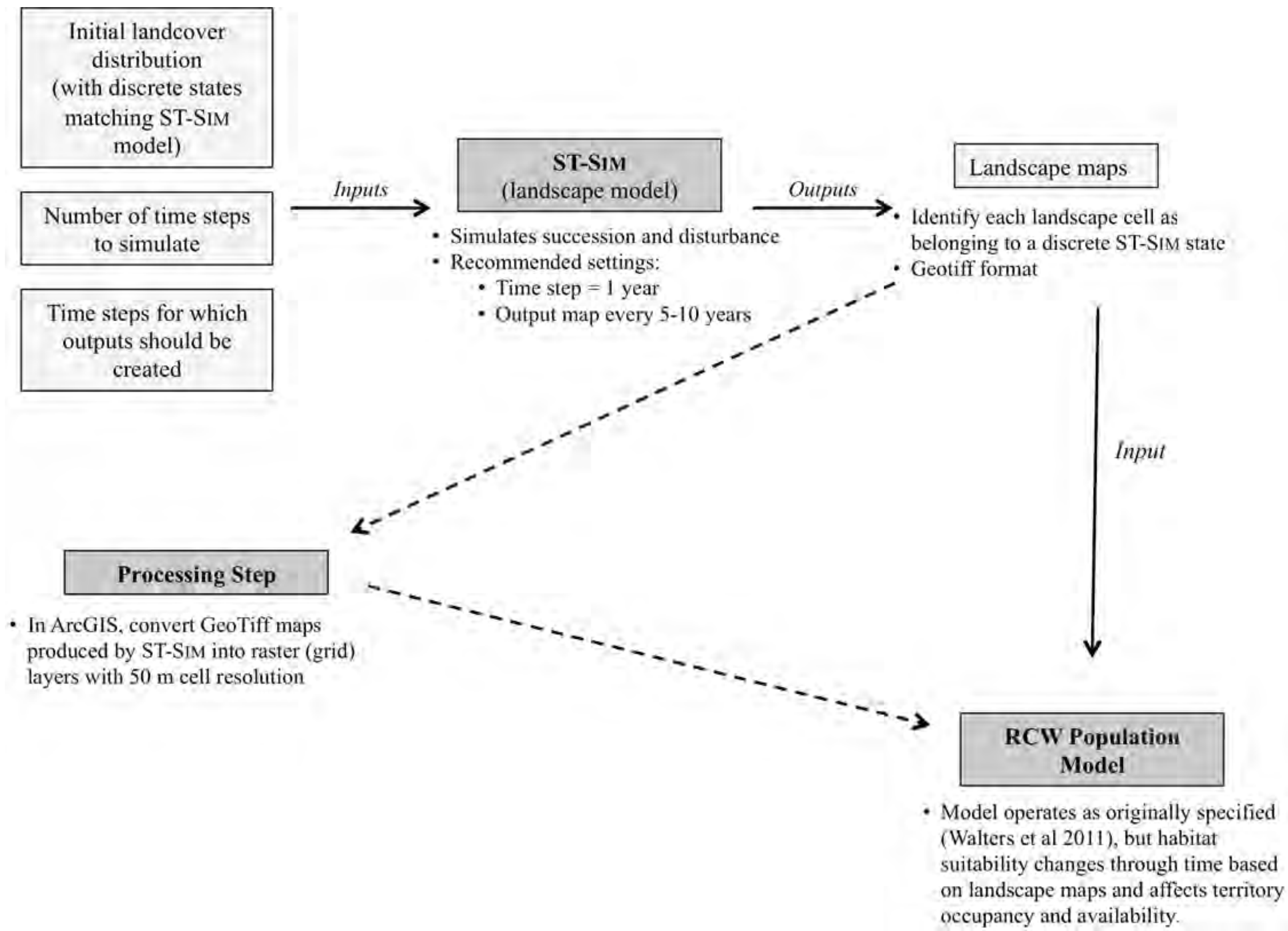


Figure 13. Conceptualization of the linked ST-SIM Landscape Model and RCW population model in the RCW DSS. The RCW DSS is intended for use as an applied tool for RCW conservation and management.

3.4.3 Modifications to the RCW Population model (version 3.0)

A previous version of the RCW population model was developed as part of SERDP Research Project RC-1472, and its parameterization and use are described fully in Letcher et al. (1998), Walters et al. (2011), and in Section 3.2 of this report. In this sub-section, we describe the ways in which the RCW model was modified in version 3.0 in order to accept ST-SIM landscape model outputs.

Input files and landscape options

As in version 2.0 (Walters et al. 2011), the RCW population model version 3.0 continues to operate as a tool bar within ArcGIS (version 10.2.2; ESRI) and requires that the user input vector shapefiles for the initial landscape and RCW cavity cluster centers. These input files are added in the first screen of the RCW DSS Wizard (Figure 14) and must be formatted as specified in Walters et al. (2011). The only modification to these input layers lies in the way the initial landscape layer is viewed by the user. In the past, the landscape remained static throughout the simulation based on the landcover types specified in this initial landscape layer. Now, however, this layer represents only the landscape configuration at the start of a simulation; the initial landscape layer characterizes the landcover only at time step 1, and landcover can change (as approximated through changes in habitat suitability) throughout the course of the simulation according to the user's specifications.

The RCW population model also now includes a tab for "Landscape Options", where the user can choose to constrain the availability of RCW territories (or cavity clusters) based on (1) nesting and foraging habitat area, (2) habitat suitability, or (3) no constraints.

Nesting and foraging habitat option

If the first radio button is selected ("Constrain using nesting and foraging habitat"; Figure 15), the model will operate with the same capabilities associated with version 2.0 of the RCW population model (Walters et al. 2011). In this case, all new territories (added as recruitment clusters or buds) must have a sufficient area of foraging habitat that is not already assigned to another territory in order to support an RCW group. That minimum amount of required foraging habitat is indicated by the user when he/she selects the radio buttons for "120", "150" or "200 acres".

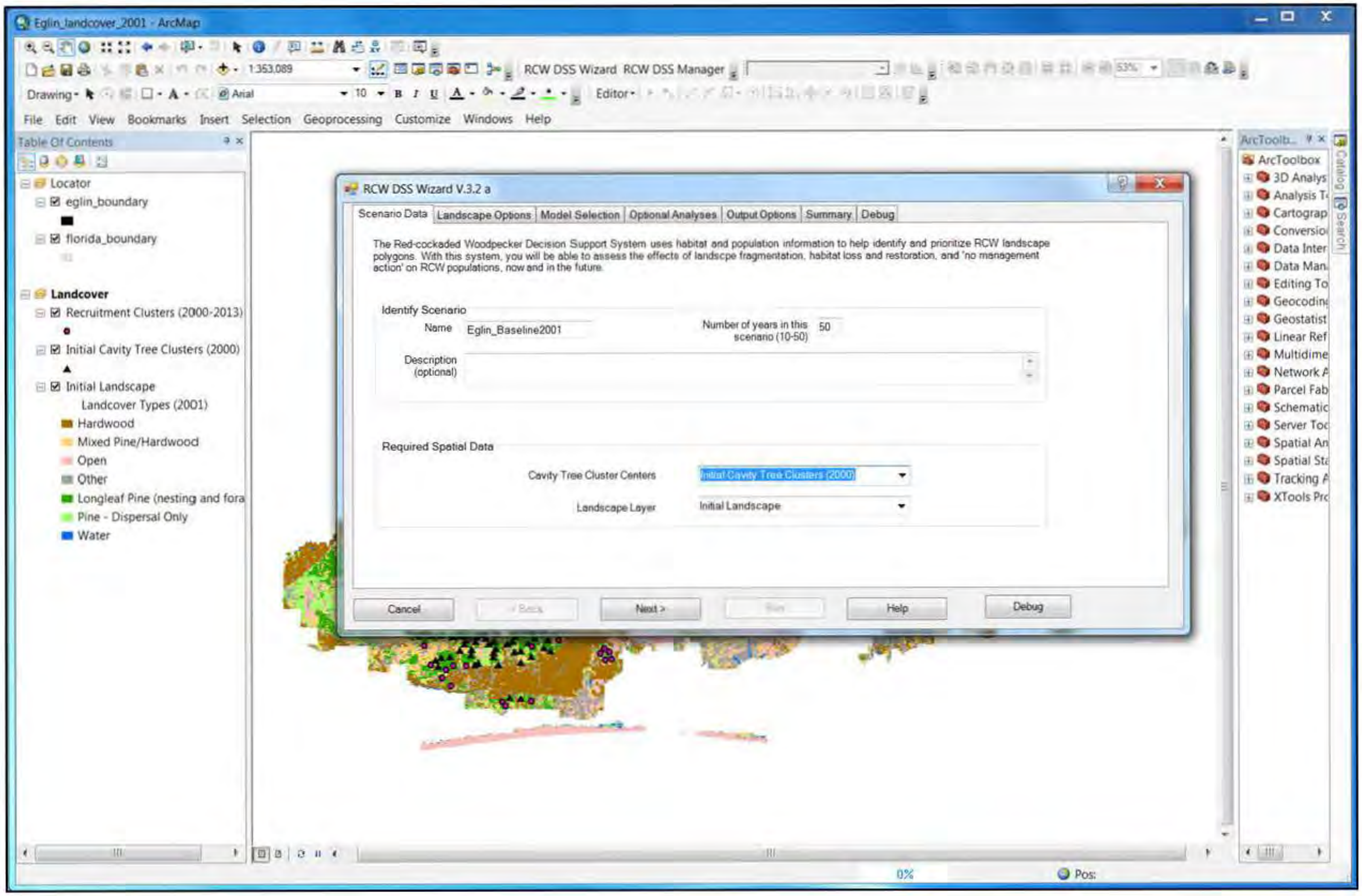


Figure 14. The Scenario Data screen in the RCW population model version 3.0, where the user delineates scenario properties, the initial landscape layer, and the initial RCW cavity cluster layer.

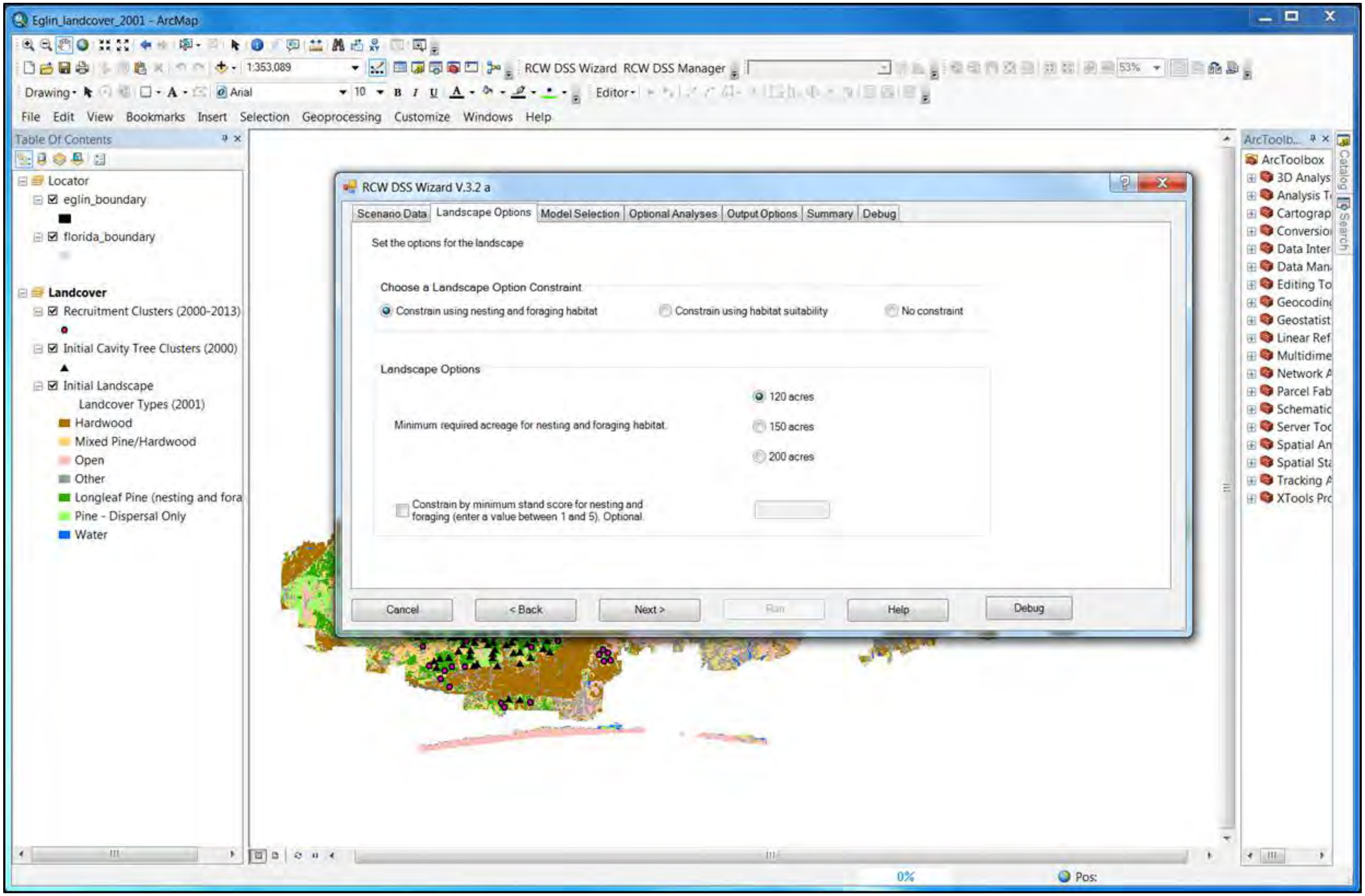


Figure 15. The Landscape Options screen for "Constrain using nesting and foraging habitat" in the RCW population model version 3.0, where the user specifies the minimum acreage required for a new RCW territory (i.e., a recruitment cluster or bud) to support a group.

Habitat suitability option

If the user wishes to operate the RCW DSS, coupling the ST-SIM landscape model with the RCW population model, he/she should select the second radio button for “Constrain using habitat suitability” (Figure 16). With this option, the model will determine whether existing RCW territories (i.e., those indicated in the initial cavity cluster layer), recruitment clusters, and buds have enough habitat to support an RCW group based on habitat suitability and territory size thresholds. Here, the user must indicate the “Minimum Habitat Suitability Score” and the “Territory area required if all habitat at minimum score” in acres in the adjacent boxes (Figure 16). These inputs, in other words, set how large a territory must be if it is composed entirely of low suitability habitat. For example, in the baseline model described for Eglin AFB in this report, landscape suitability ranges from 1 (marginally suitable) to 5 (highly suitable; Figure 7). Based on the actual density of RCW territories between 2000 and 2013 and the area/configuration of landcover types in 2001 at Eglin AFB, we determined that the smallest territory of poor quality (i.e., if the area-weighted average habitat suitability for that territory was 1; see Appendix E2 for more information on this calculation) was 120 acres. Therefore, in this example, we would parameterize the model such that the Minimum Habitat Suitability Score = 1 and the Territory area required if all habitat is at minimum score = 120 acres.

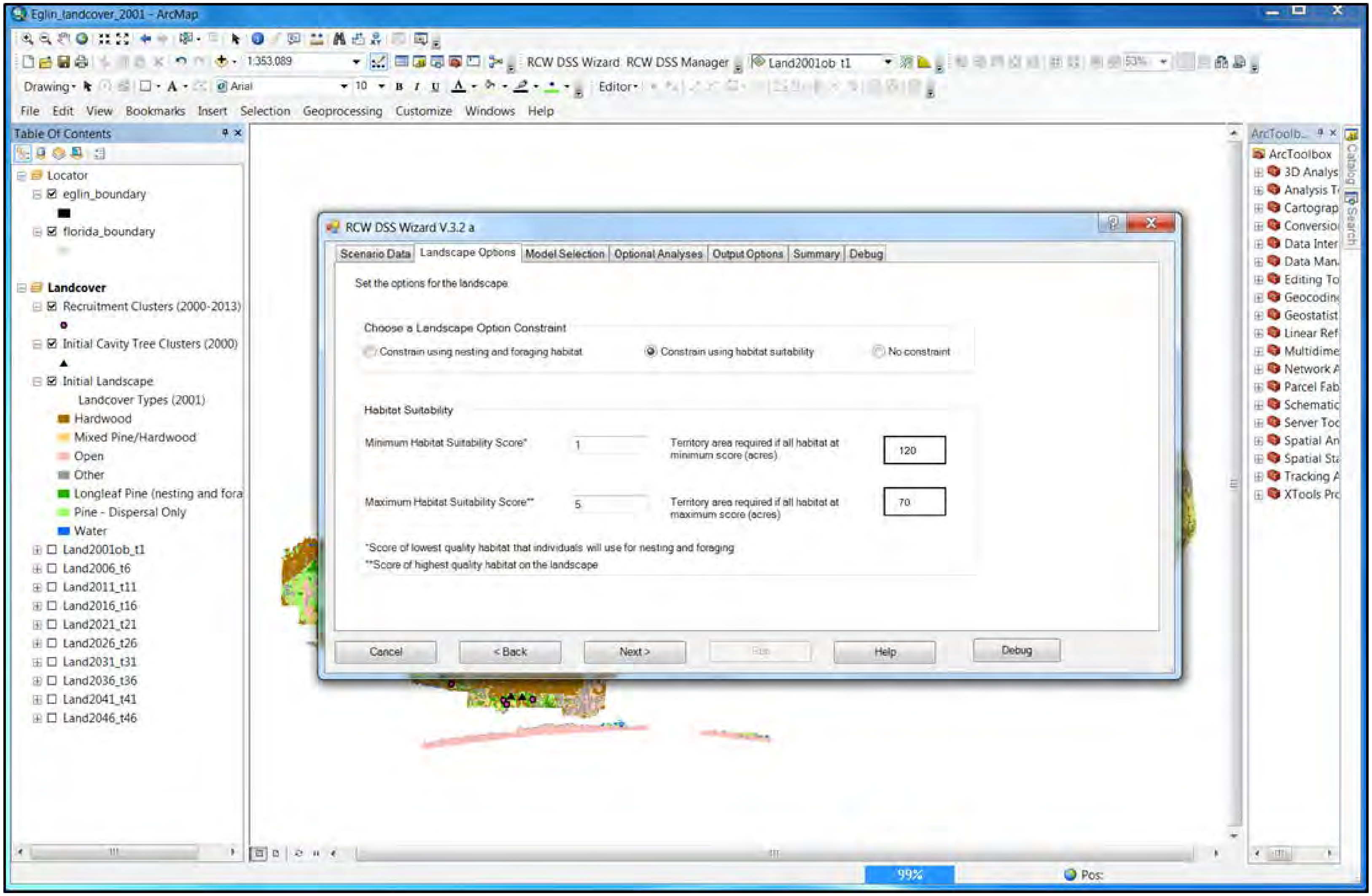


Figure 16. The Landscape Options screen for "Constrain using habitat suitability" in the RCW population model version 3.0, where the user constrains the ability for a given territory to support an RCW group based on the underlying habitat suitability. To use this option, a user must add raster maps of landscape states associated with RCW habitat suitability to the ArcGIS project. This is the option that a user should select in order to consider changing habitat suitability through time within the RCW DSS (joining the ST-SIM landscape model and the RCW population model).

The user must also indicate how small a territory can be if that territory is composed entirely of highly suitable habitat in the boxes adjacent to “Maximum Habitat Suitability Score” and “Territory area required if all habitat at maximum score (acres)”, respectively. Continuing with the example described in the previous paragraph, we estimated that the smallest territory when habitat was of very high quality (i.e., if the area-weighted average habitat suitability for that territory were 5; see Appendix E2 for more information on this calculation) was 70 acres. Therefore, in this example, we would parameterize the model such that the Maximum Habitat Suitability Score = 5 and the Territory area required if all habitat at maximum score = 70 acres.

When using the Habitat Suitability option, the user must also add one or more landscape state files created through the ST-SIM landscape model into the ArcGIS project (in addition to the initial landscape and RCW cavity cluster shapefiles). These additional landscape files must be in raster format with a 50 m cell resolution, have state identifiers identical to those used in the ST-SIM landscape model (Appendix D), and have the same coordinate system as the initial input shapefiles described above. Each landscape file name must also end in “_t<time step>”, where the value given in place of “<time step>” indicates the model time step at which point the new landscape map should be evaluated. For example, if the user adds a raster named “Landscape_t5” to the ArcGIS project, then habitat suitability values would change to those associated with this raster’s landcover states at time step 5.

To employ this option, the user must also always provide a landscape state file for time step 1 (e.g., “Landcover_t1”) to indicate habitat suitability at the start of the model. From there, any number of additional landscape state files can be added to the model. For example, if the user includes the files “Landcover_t1”, “Landcover_t5”, “Landcover_t7”, and “Landcover_t8” for a simulation with 10 time steps, suitability would initially be based on the state types given in “Landcover_t1”, and the model would re-evaluate suitability at time steps 5, 7, and 8 based on the states given in “Landcover_t5”, “Landcover_t7”, and “Landcover_t8”, respectively. The final 2 time steps of the simulation would continue to consider the suitability values associated with states given in “Landcover_t8”.

At the start of a simulation that utilizes the Habitat Suitability option, the RCW population model will create Theissen polygons around all initial territories and recruitment clusters, using the “Landcover_t1” landscape file to calculate an area-weighted suitability score for each territory within the confines of its Theissen polygon. In addition, using the user-specified minimum and maximum suitability scores and their associated territory areas, the model will use the formula for a straight line (Y = mX + B) to calculate threshold area values (Y, in acres) for every suitability score (X) between the minimum and maximum values specified by the user (Appendix E2). The model will then compare each territory’s area with the calculated threshold area associated with its area-weighted average suitability score. If a territory’s area is less than the threshold area required, the model assumes that the territory is not large enough or of high enough quality to support a group of RCWs, and no birds will be allowed to reproduce at that location. This process is repeated at each time step during which the landscape suitability layer changes.

In some simulations, a territory may support an RCW group at time step t but not at time step $t+1$ due to changes in the territory’s average suitability. In this case, all RCWs previously in that territory will become Floaters at time step $t+1$, with the exception of the male breeder. Male breeders will remain on the territory until they die but will be unavailable for further interaction (i.e, breeding, movement to other territories) in the model. In addition, the territory will be removed as an option for occupancy by neighboring birds for the remainder of the simulation. In

contrast, an area may be unsuitable for the placement of new RCW territories (i.e., buds) at time step *t*, but, due to changes in the landscape, this habitat may become suitable enough to support an RCW group at time step *t+1*. In this case, the model could place a budded RCW territory at that location at time step *t+1*.

No constraints option

Finally, the user can elect to click on the radio button for “No constraints” in the “Landscape Options” tab (Figure 17). This is also a new option added since version 2.0 and allows the user to add recruitment clusters and buds without considering a minimum territory area or habitat suitability. Under this condition, recruitment clusters and buds can go anywhere on the landscape (as long as two territories do not overlap or occupy the same location). This option is the least conservative of the simulation options and should be used with caution.

Aside from the landscape options, the remaining inputs, simulation options, program routines, and available outputs are identical to those associated with previous versions of the model (Walters et al. 2011).

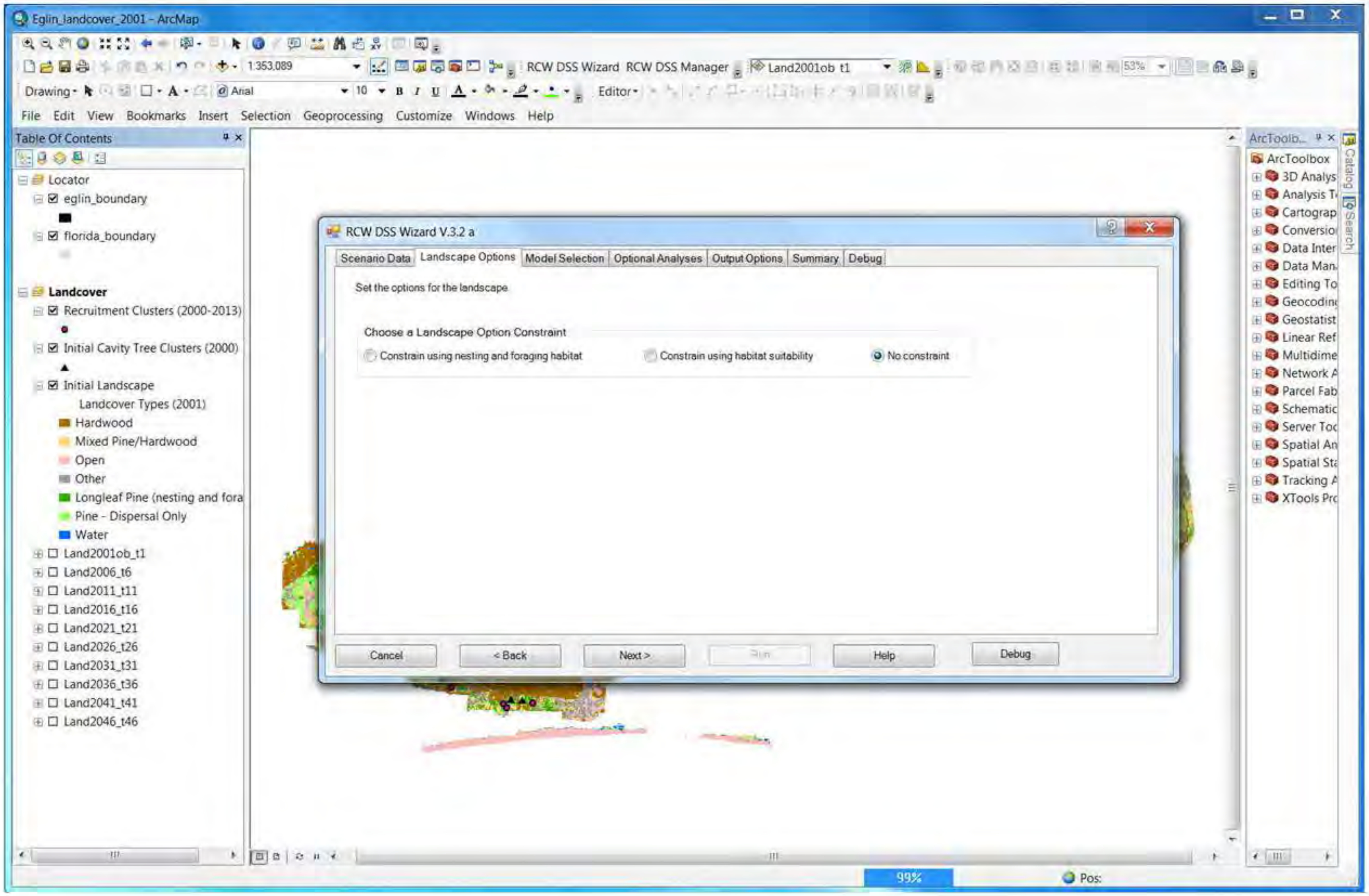


Figure 17. The Landscape Options screen for "No constraints" in the RCW population model version 3.0, where the addition of new RCW territories is not constrained by a minimum area or habitat suitability.

3.4.4 Validation methodology of the RCW DSS

Reference RCW population data

Empirical values used to validate RCW DSS predictions were extracted from an existing database (i.e., the "Eglin RCW database") collated during an ongoing project at Eglin AFB that spanned the years 1990 to 2013 inclusive (Walters unpublished data; see Walters et al. 1988 and Walters 2004 for population monitoring methods). From this database, we determined the number of territories that were occupied by either a solitary male or a breeding pair for each year between 2000 and 2013, which increased steadily from 295 to 479 occupied territories over this time period (Table 5). We compared these observations to the number of occupied territories for equivalent years as predicted by the RCW DSS for validation purposes. Other population characteristics, such as population size and composition, were not used for validation, because these data were not available for the entire population at Eglin.

Table 5. Results of model validation for the RCW DSS using the number of territories occupied by either a solitary male or a breeding pair at Eglin AFB from 2000 to 2013. The mean and variance of the standard deviates are given under the validation methodology recommended by McCarthy and Broome (2000).

Year	**Number of Occupied Territories (Observed)**	**Average Number of Occupied Territories (Predicted)**	**Standard Deviates**
2000	295	295	-------------
2001	303	306	0.52
2002	302	320	1.51
2003	306	332	1.62
2004	310	346	2.22
2005	316	359	2.32
2006	341	372	1.60
2007	360	389	1.54
2008	384	404	1.00
2009	415	417	0.10
2010	424	430	0.30
2011	438	442	0.21
2012	455	455	0.002
2013	479	467	-0.65
Mean of Standard Deviates			0.95 $t = 3.68$ p-value = 0.003
Variance in Standard Deviates			0.86 x-square = 10.35 p-value = 0.83

RCW DSS simulation

We first ran the baseline simulation in the ST-SIM landscape model for 12 time steps, using the 2001 reference landcover state layer (Appendix E1) to represent initial landcover

conditions and the baseline parameters discussed in Section 3.3. From this simulation (which was validated in Section 4.3 for the years 2001 to 2010), we exported predictive landcover state maps that approximated conditions in 2005 and 2010. Because the validation results for the baseline ST-SIM landscape model in Section 4.3 showed that there was little variation between stochastic, iterative simulations and that all outputs from the 10 iterations analyzed had ~ 84% accuracy level (Table 22), we only simulated and used one iteration of the landscape model in the RCW DSS. We converted the predictive landcover state maps from GeoTiff files (i.e., the original format for outputs produced by the ST-SIM landscape model) to rasters with a 50 meter resolution in ArcGIS. We renamed these predictive landcover layers to indicate the years at which each layer should be considered in the RCW population model (e.g., layer representing landcover in 2005 = "Land05_t5", layer representing landcover in 2010 = "Land10_t10").

We then parameterized a scenario within the RCW population model. We used the Initial Cavity Tree Cluster and Recruitment Cluster layers for Eglin AFB described in Section 3.2 (representing RCW territories in 2000 and from 2001-2013, respectively; Figure 6). We also used the Initial Landscape Layer for Eglin described in Section 3.2, which was created based on a classification of remotely sensed satellite imagery from 2001 (Appendix E1; Figure 6). We used the 2001 reference landcover map in its original raster format with a 50 m cell size (showing landcover in the ST-SIM states) as the initial suitability layer in the RCW population model (renamed "Land01_t1"). The raster files converted from the predictive ST-SIM landscape model outputs, "Land05_t5" and "Land10_t10", were added to the ArcGIS project to simulate changes in habitat suitability within the RCW population model at time steps 5 and 10, respectively.

Finally, we selected the "Constrain using habitat suitability" landscape option with a "Minimum Habitat Suitability Score" equal to 1, a "Territory area required if all habitat at minimum score" equal to 120 acres, a "Maximum Habitat Suitability Score" equal to 5, and a "Territory area required if all habitat at maximum score" equal to 70 acres (Appendix E2). We parameterized the mean group size as 2.5 in accordance with an actual average group size of 2.52 observed in the region (Walters, unpublished data). This value also influenced how occupied territories were populated; with this average group size, 90% of all occupied territories were populated with a breeding pair, 50% of that 90% (45% of all territories) were populated with a single male helper, and 10% of the territories that contained one helper were populated with a second male helper (4.5% of all territories). We selected the demographic rates associated with the Coastal type locality. Although these demographic rates were originally based on observations of the RCW population at MCBCL, RCW populations at Eglin AFB exhibit similar survival and reproductive rates (Appendix B-4).

We simulated the RCW population model for 13 times steps (2000 to 2013) and 20 iterations, ultimately noting the predicted number of occupied territories, population size, number of solitary males, and number of breeding pairs for each time step. We conducted 20 iterations instead of the full 70 due to computer processing and memory limitations. We labeled this scenario the "Habitat Constraints scenario". In addition to this scenario, we also simulated the dynamics of the RCW population at Eglin AFB in a second scenario (i.e., the "No Constraints scenario"), where we selected the "No constraints" landscape option (Figure 17). We otherwise used identical RCW population model parameters employed in the DSS Validation Scenario, with the exception that we changed the landscape option selected, did not add the additional landscape suitability layers, and conducted simulations for the full 70 iterations. We compared the results of these two scenarios with that of the scenario simulated in Section 3.2

(henceforth, the “Foraging Constraints scenario”), where we selected “Constrain using nesting and foraging habitat” as the landscape option (Figure 15) with a minimum acreage of 150 ac. We compared the results of these three scenarios to better understand how different considerations of habitat availability influence population projections.

Validation

Because we used predictive landcover maps generated by the ST-SIM landscape model within the RCW population model, validating the results of the DSS Validation Scenario against actual territory occupancy data is indicative of the performance capabilities of the RCW DSS. Following the methodology of McCarthy and Broome (2000), we calculated a standard deviate for the predicted (i.e., through the Eglin DSS Validation Scenario) and observed number of occupied territories for each year (2001-2013). In general, if a model output is predicted accurately, then the standard deviate will have a mean equal to zero and a variance equal to one. We used a t-test to determine if the mean of the standard deviates for the number of occupied territories was significantly different from zero and a chi-squared test to determine if the variance was significantly different from one. We assumed significance at a level of $p < 0.01$. We adopted a strict p-value threshold for this analysis due to the complexity of model inputs and routines. This method tests the accuracy of both the mean and variance in predicted model outputs. All data analyses were performed in R (R Development Core Team 2014).

3.5 DSS management applications

Given the results of validation exercises described in Sections 4.2 through 4.3, the ST-SIM landscape model, the RCW population model, and the RCW DSS each offer robust representations of longleaf pine ecosystem and/or RCW population dynamics at Eglin AFB. As such, these models – either alone or linked in the RCW DSS – can offer powerful tools for informing decisions regarding landcover change and management on the base. In this section, we discuss several applications of the RCW DSS that exemplify how base natural resource managers could use this tool to make efficient, scientifically informed decisions with regard to endangered species habitat and population management while complementing related DOD goals, such as training and readiness planning. In general, the RCW DSS can be used to evaluate the impacts of (*i*) maintaining status quo management regimes, (*ii*) altering landscape management techniques, targets, or application locations; (*iii*) removing existing habitat for base development projects; and (*iv*) assessing other landscape-mediated threats.

3.5.1 Methodology

Initial model parameterization

To exemplify some of the ways in which the RCW DSS can be used by natural resource managers, we compared the results of a series of scenarios. These scenarios, except where noted, were initialized with parameters associated with 2010/2013 landscape and RCW population conditions at Eglin AFB.

For the ST-SIM landscape model, we parameterized the model with the 2010 reference landscape state layer described in Appendix E1 (Table 4; Figure 12a). We operated the landscape model under baseline conditions (Section 3.3; Appendix D) for each scenario except where noted below. For each scenario, we simulated the landscape model for 30 time steps and exported predictive GeoTiff landcover maps in 10-year intervals to describe likely conditions in the years 2020, 2030, and 2040 under several alternative landscape management regimes. Predictive

GeoTiff maps were then converted to raster layers with 50 m resolution for use as suitability layers in the RCW population model.

We then reclassified the 2010 landcover map (used previously to create the 2010 reference landcover state map; Appendix E1) to landcover types recognized by the RCW population model (Table E1-1) and converted this layer to a polygon (Figure 18). We used this layer as the initial landscape layer for all RCW population model scenarios. The 2010 reference landcover state map (50 m resolution; Appendix E1) was similarly used as the initial suitability layer in the first time step for every RCW population model scenario. The initial cavity cluster layer, used to delineate the locations of RCW territories at the start of all model scenarios, was created from the geographic coordinates of 520 known RCW territory centers at Eglin AFB in the year 2013. These territory locations were extracted from an existing database (i.e., the "Eglin RCW database") collated during an ongoing project at Eglin AFB that spanned the years 1990 to 2013 inclusive (Walters unpublished data; see Walters et al. 1988 and Walters 2004 for population monitoring methods). Because these simulations are completely predictive in nature, we did not add additional recruitment clusters.

Finally, for all scenarios in the RCW population model, we also selected the "Constrain using habitat suitability" landscape option with a "Minimum Habitat Suitability Score" equal to 1, a "Territory area required if all habitat at minimum score" equal to 120 acres, a "Maximum Habitat Suitability Score" equal to 5, and a "Territory area required if all habitat at maximum score" equal to 70 acres (Appendix E2). We parameterized the mean group size as 2.5 in accordance with an actual average group size of 2.52 observed in the region (Walters unpublished data) and selected the demographic rates associated with the Coastal type locality. We simulated the RCW population model for 30 times steps (predicting population dynamics from 2010 to 2040) and 20 iterations, ultimately noting the predicted number of occupied territories, population size, number of solitary males, and number of breeding pairs for each time step.

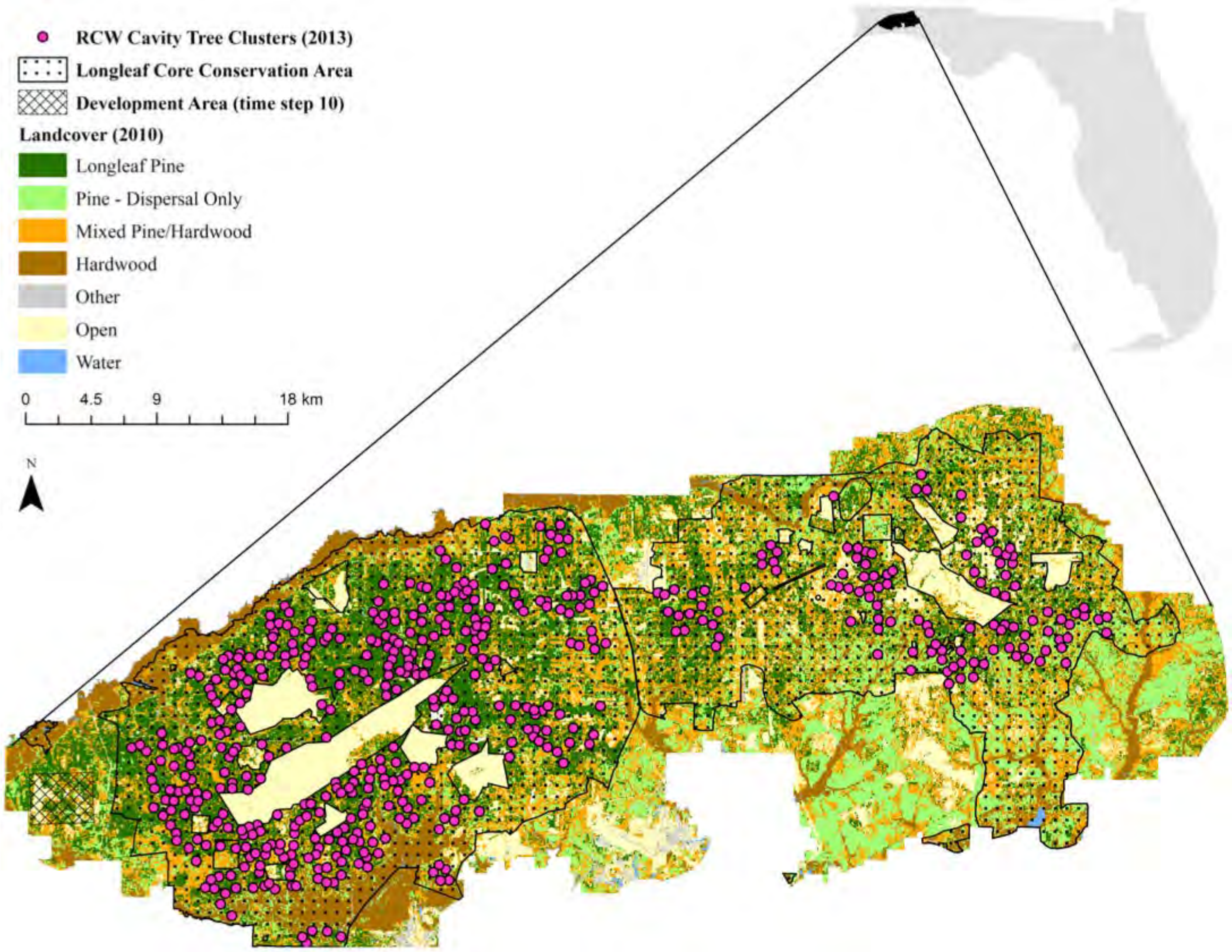


Figure 18. Initial landcover and RCW cavity cluster centers used within the RCW DSS for all scenarios. The development area and longleaf conservation core areas shown here were used to constrain specific transitions within the ST-SIM landscape model for the "Development" and the "Core Conservation Area" scenarios, respectively, described in Section 3.5.

Model scenarios

The parameters and initial layers described in the previous section were used in all scenarios except where noted in the individual scenario descriptions:

Status Quo and No Management scenarios

In the "Status Quo scenario", we assumed that all landscape management regimes and targets would continue unchanged into the future. Therefore, we simulated the ST-SIM landscape model for 30 years under baseline conditions, using the predictive landscape state layers in the RCW population model to determine long-term RCW population dynamics in response to the current management regime within the RCW DSS. The results of the Status Quo scenario also provided baseline landcover state distributions and RCW population dynamics with which to compare the results of other scenarios.

In contrast to the Status Quo scenario, we simulated a second scenario where all management targets were set to 0 acres in the "No Management scenario". In this scenario, we

assumed that only wildfires could reset successional pathways back to more suitable states for RCWs and that prescribed burns, mechanical removal, and herbicide treatments would not have an impact on the landscape at Eglin AFB.

Altered fire regime scenarios

In a series of scenarios, we investigated the impacts of varying the fire regime at Eglin AFB. In two scenarios, we changed the prescribed burn management target in the ST-SIM landscape model from the current (status quo) target of 104,000 acres per year to the following:

- "Fire 50K scenario": the amount of area burned annually on the base is roughly halved to 50,000 acres per year.
- "Fire 200K scenario": the amount of area burned annually on the base is roughly doubled to 200,000 acres per year.

We also examined the impact of altering the targeted landcover type for prescribed burns. In the Status Quo scenario, we assumed that prescribed fire would be concentrated in longleaf pine states that were already of higher quality (i.e., with high or moderate midstory suitability and high groundcover density) according to actual fire dynamics on the base (Eglin AFB Fire Management Data; Hiers, pers. comm. 2010). In the "Fire Restoration scenario", we assumed that less suitable longleaf pine states (i.e., with moderate or low midstory suitability and low groundcover density) would be preferentially burned (Table 6). In this scenario, we ultimately investigated whether focusing limited fire resources on maintaining suitable habitat would be more or less beneficial for RCW populations than focusing those resources on restoring degraded areas.

Table 6. The probability that a prescribed fire would occur in a given longleaf pine landcover state in the ST-SIM landscape model in (i) the Status Quo (or Baseline) scenario compared to (ii) the New Fire Probability scenario. Probabilities for each combination of midstory suitability and groundcover density are the same for all canopy BAs (Table 2; Figure 7).

Longleaf Pine Age	**Midstory Suitability**	**Groundcover Density**	**Status Quo Scenario Probability**	**New Fire Probability Scenario Probability**
15-59 years	High	High	0.075	0.05
15-59 years	High	Low	0.075	0.05
15-59 years	Moderate	High	0.075	0.05
15-59 years	Moderate	Low	0.05	0.075
15-59 years	Low	Low	0	0.075
≥ 60 years	High	High	0.10	0.075
≥ 60 years	High	Low	0.10	0.075
≥ 60 years	Moderate	High	0.10	0.075
≥ 60 years	Moderate	Low	0.075	0.10
≥ 60 years	Low	Low	0	0.10

Other management changes

In the "Longleaf Core Conservation Area (LCCA) scenario", we examined how the RCW population would be affected if all management resources were confined within the boundaries

of the LCCA (Figure 18). This area was delineated from the forest compartment boundaries in the Integrated Natural Resources Management Plan's longleaf restoration priority area, which represents the minimal area that should be managed for longleaf pine ecosystems and incorporates all fire-dependent endangered species populations necessary for meeting their recovery goals at Eglin AFB. This area is often used to prioritize limited management resources (e.g., fire, longleaf planting, etc.) to maximize restoration efforts by concentrating them in one area of the base.

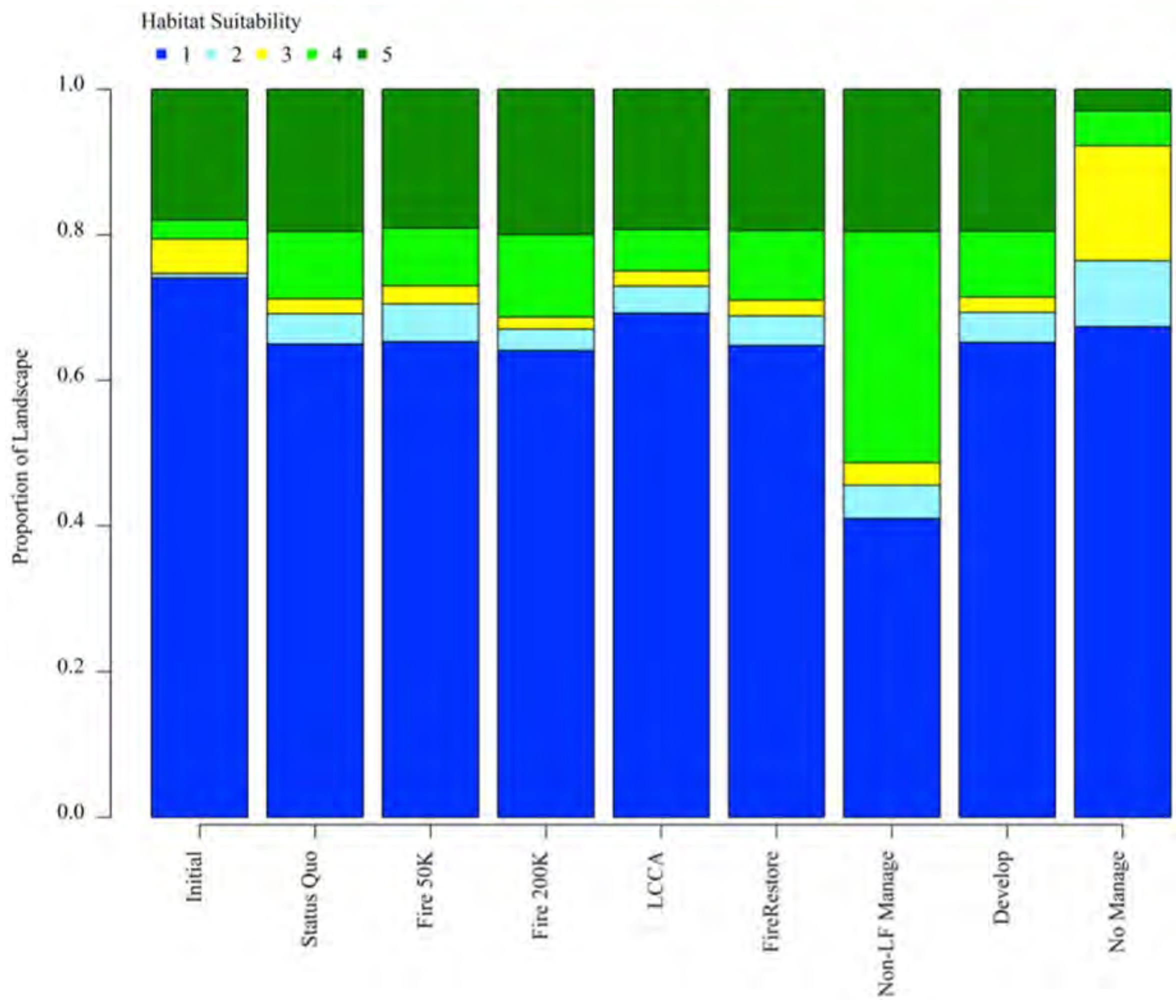
In the next scenario, the "Non-Longleaf Management scenario", we examined the impacts of more aggressively restoring hardwood, mixed, and sand pine forest types at the expense of restoring or maintaining a wider area of Eglin AFB. In the Status Quo scenario, we assumed that 104,000 acres, 1,000 acres, and 7,000 acres of the base would be treated with prescribed burns, herbicide, and mechanical midstory removal, respectively, each year and that longleaf pine states would preferentially receive all management actions. In the Non-Longleaf Management scenario, we assumed that the area treated with herbicide and mechanical midstory removal would double (to 2,000 and 14,000 acres, respectively) at the expense of prescribed fire (reduced to 50,000 acres) and that the probability of Hardwood, Mixed, and Sand Pine landcover states experiencing these management actions would increase (to a probability of 0.1). Therefore, in this scenario, more resources would be allocated to herbicide and mechanical removal while non-longleaf pine states would preferentially receive that management.

Development

In the "Development scenario", we simulated the impact of a hypothetical development project on the RCW population at Eglin AFB. In this simulation, we forced the transition of all landcover states within a 36,736 acre plot in the western half of the base (Figure 18) to the Developed landcover state. This is not a proposed development project on the base and only serves as an example of how the RCW DSS could be used to evaluate the impacts of proposed development projects.

Statistical analyses

To evaluate whether changes to the baseline management regime have significant impacts on the availability of RCW habitat, we categorized the landscape state classes by suitability value and determined the total area of the landscape in each suitability class (from low suitability = 1 to high suitability = 5) in the final model year (2040). We did this for each model scenario, ultimately producing landscape distributions according to habitat suitability value (Figure 19). We then compared the habitat suitability distribution for each model scenario to that of the Status Quo scenario to determine if model scenarios depicting alternative management regimes produced significantly higher or lower amounts of high quality habitat for RCWs compared to the current regime. This test is generally applied to a frequency count for a single categorical variable (i.e., the area of the landscape falling into each suitability class) from two different populations (i.e., the results of the Status Quo scenario versus other scenarios). We rejected the null hypothesis (i.e., that the area distributions for the Status Quo scenario and other management scenarios were the same) at a significance level $p < 0.01$. All data analyses were performed in R (R Development Core Team 2014).



[1]Management scenarios included:

- Status Quo: no changes to the current landscape management regime (i.e., the baseline ST-SIM model);
- Fire 50K: annual target of 50,000 acres for prescribed burning (50% of Status Quo target);
- Fire 200K: annual target of 200,000 acres for prescribed burning (twice the Status Quo target);
- LCCA: all prescribed burning confined to the area of the Core Conservation Area (Figure 18);
- FireRestore: areas of lower suitability are preferentially burned at the expense of maintaining areas of higher suitability;
- Non-LF Manage: a higher area of hardwood and mixed forest stands are treated with herbicide and mechanical midstory removal at the expense of managing longleaf pine stands;
- Develop: all habitat within a specific 3,676 acre plot is lost to development (Figure 18);
- No Manage: the landscape is not managed in any way (no prescribed burning, herbicide, or mechanical midstory removal).

Figure 19. ST-SIM landscape model predictions for the proportion of low (value = 1, dark blue) to high (value = 5, dark green) suitability habitat for RCWs at Eglin AFB after 30 years under several management scenarios[1]. The landscape model was initialized under the same starting conditions (the “initial” bar on far left) for all scenarios.

4. Results and Discussion

4.1 Field studies
4.1.1 Treatment effects on vegetation over time
Ground cover composition and diversity measures

The ground cover composition of restoration treatment sites differed in ordination space from that of reference sites prior to treatment applications (Figures 20, 21). Between 1994 and 2010 all treatment sites moved in a trajectory toward the original reference conditions in NMDS space, but reference sites also changed in species composition over that time (Figure 22). The number of prescribed burn events per site was positively correlated with the direction of compositional change towards reference conditions, whereas total overstory hardwood density, and the overstory hardwood density of turkey oak and bluejack oak per site were negatively associated (Figure 22), as expected given that treatments removed hardwood stems. Notably, three treatment sites (one of each restoration treatment) fell within the 90% confidence ellipsoid of both 1994 (pre-treatment) and 2010 reference conditions (Figure 23). Based on the *PerMANOVA* analysis of the ground cover vegetation matrix, dispersion of sample units in ordination space differed between reference sites and treatment sites for all years, indicating that reference sites were more similar to each other in composition than treatment sites ($p<0.05$). In the one-way *PerMANOVA* analysis in which blocks were not included (Appendix B-5) there were significant differences among treatments after 1996, but these differences were not significant when blocks were included (Appendix B-6) and were not the focus of the second *PerMANOVA* analysis, which centered on differences between reference and treatment sites.

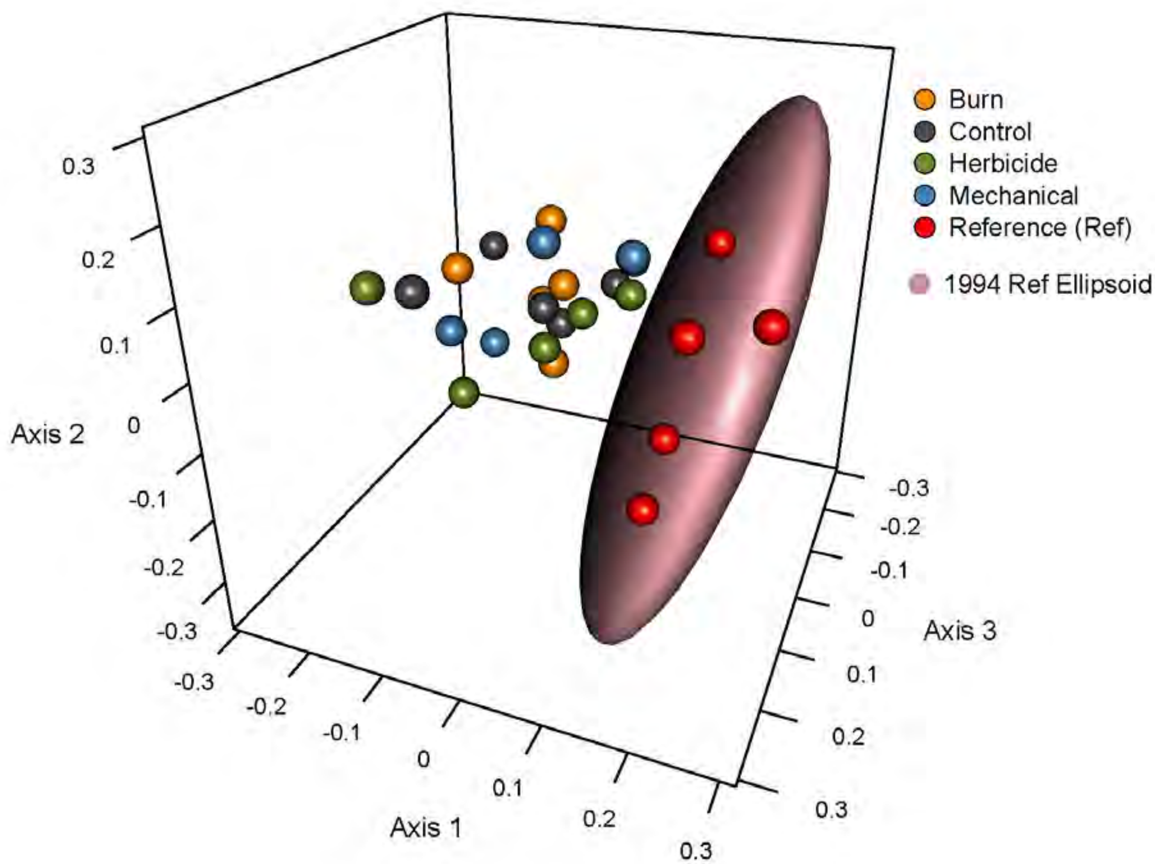


Figure 20. Three-dimensional NMDS ordination of pre-treatment and reference sites (sites shown by treatment) at the initiation of the study in 1994. A 90% confidence ellipsoid for reference conditions in 1994 is shown in pink. The NMDS ordination had a stress value of 12.15 and a non-metric fit of 0.985.

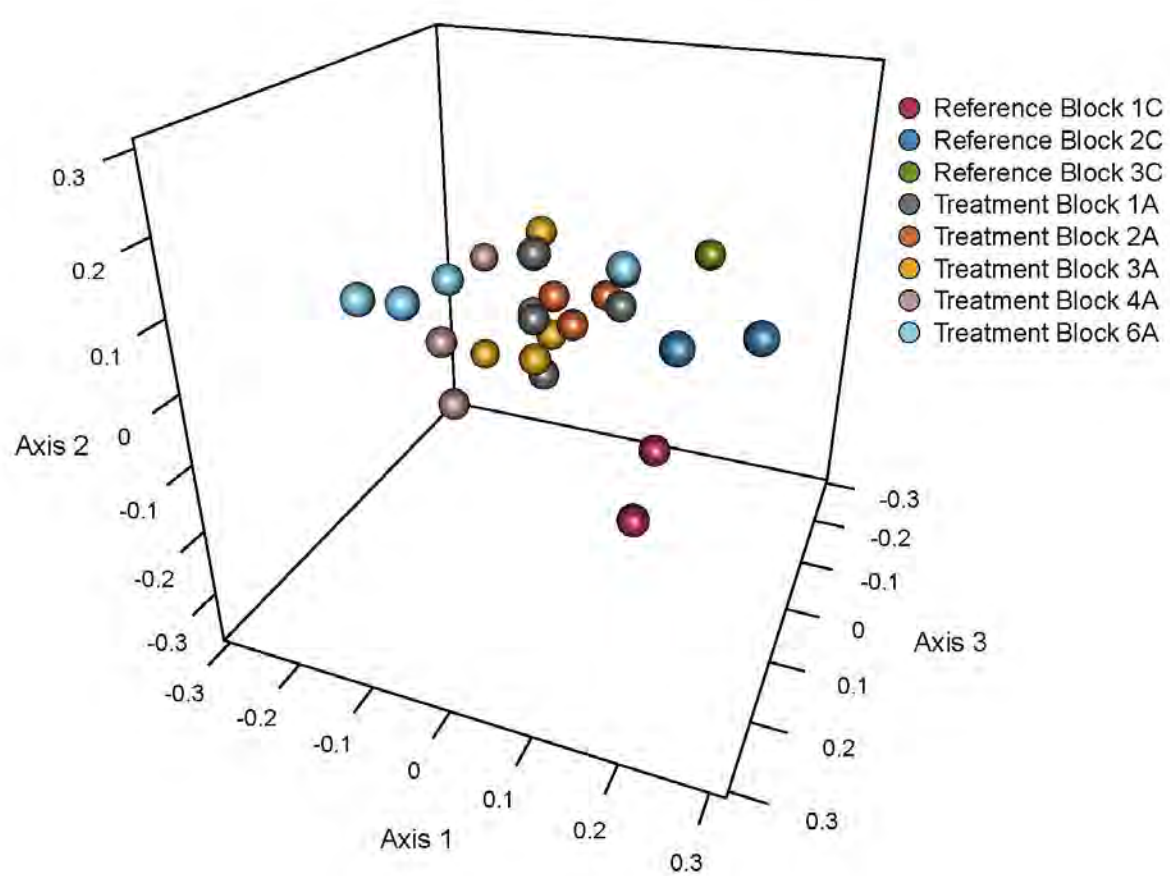


Figure 21. Three-dimensional NMDS ordination of pre-treatment and reference sites (sites shown by block) at the initiation of the study in 1994. The NMDS ordination had a stress value of 12.15 and a non-metric fit of 0.985.

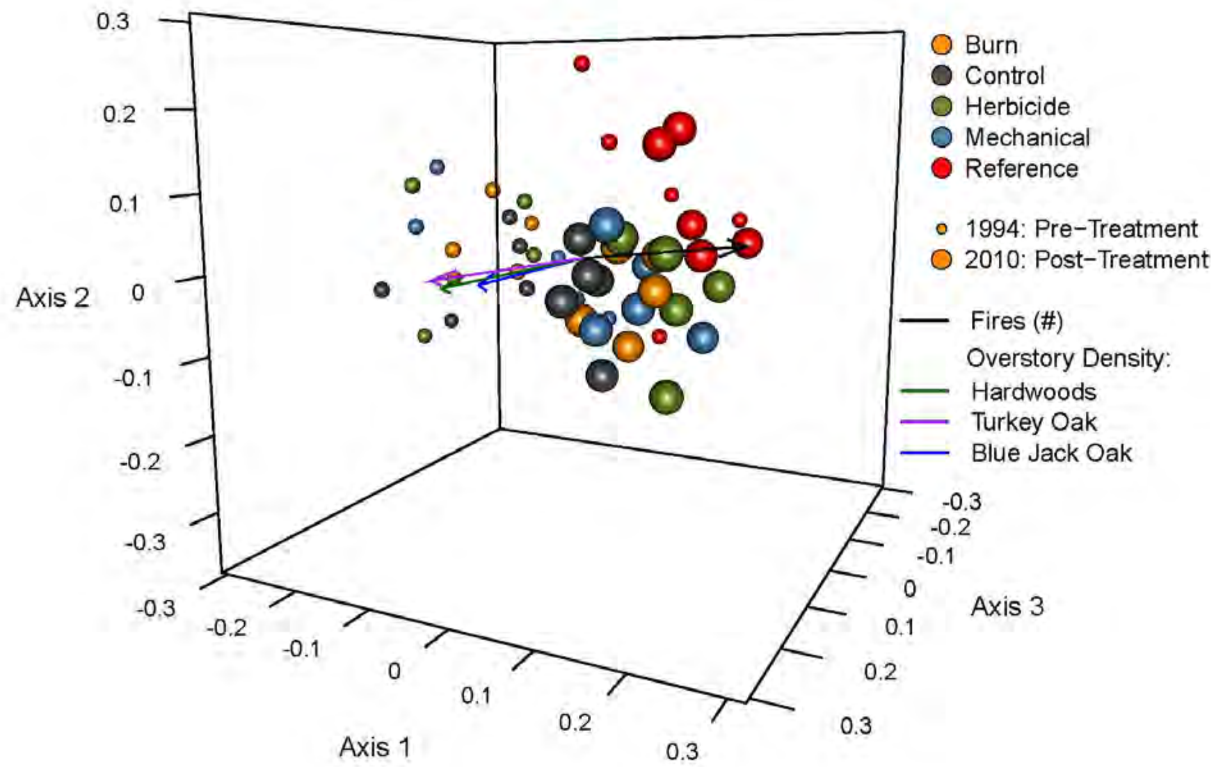


Figure 22. Three-dimensional NMDS ordination of treatment and reference sites at the initiation of the study (1994) and 15 years post-treatment (2010). The ancillary variables most significantly correlated with the ordination ($p < 0.001$) are shown as vectors. The NMDS ordination of the 1994 and 2010 data had a stress value of 13.79 and a non-metric fit of 0.981.

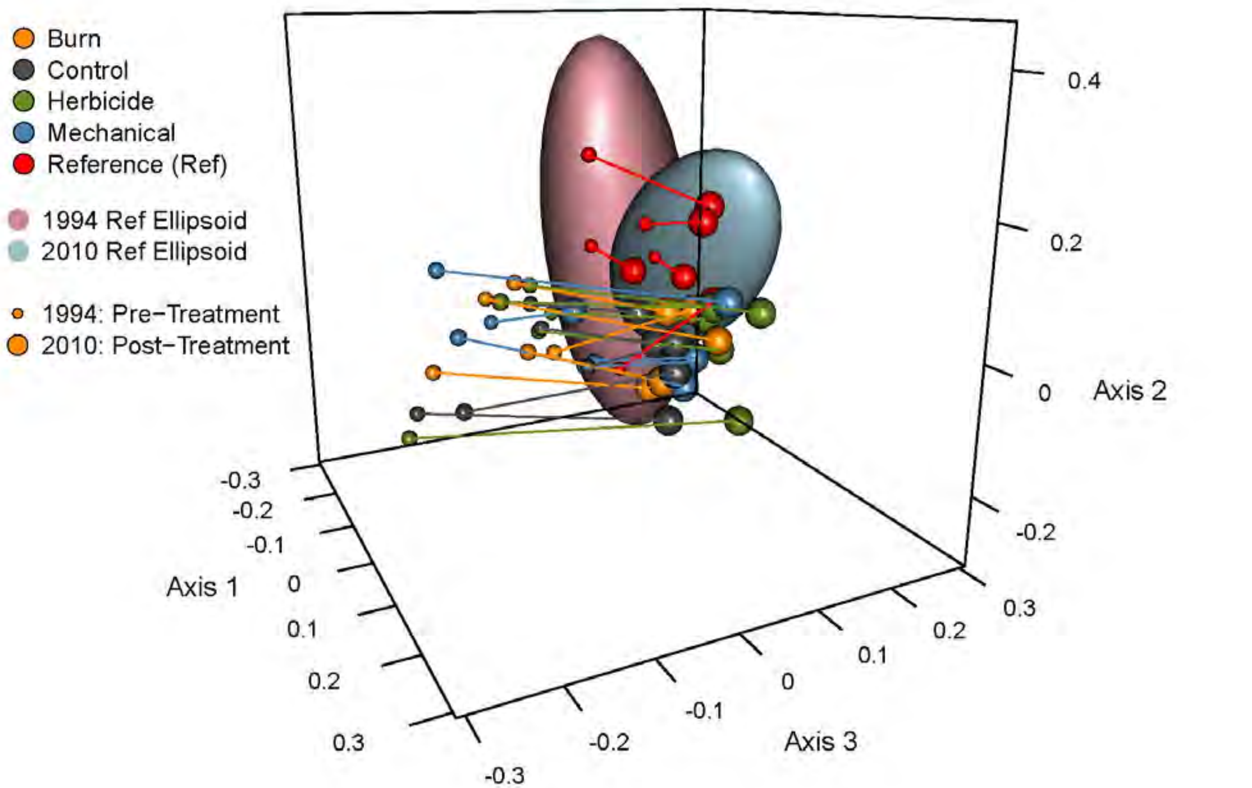


Figure 23. Three-dimensional NMDS ordination of all six years of vegetation data from 1994 to 2010 with 90% confidence ellipsoids for 1994 reference conditions (pink) and 2010 reference conditions (blue). The ordination had a stress value of 16.86 and a non-metric fit of 0.972. Change vectors are shown to illustrate how the sites moved over time in species composition space in relation to reference conditions and to each other.

Regardless of restoration treatment, the PS to reference sites increased between 1994 and 2010 ($p<0.001$). Post-treatment, the burn treatment sites were different ($p< 0.05$) from herbicide and control sites in some years immediately following treatment (Figure 24, Appendix B-7). Differences in mean ground cover species richness existed at the treatment scale between burn and herbicide sites, burn and control sites and mechanical and control sites in the initial post-treatment period (1995-1998) with burn sites more similar to reference conditions (Figure 25, Appendix B-8). At the plot scale, herbicide treatments had significantly lower species richness than the control, burn, and mechanical sites from 1995 to 1998, but these differences were no longer apparent in 2010 (Appendices C-1 and B-9). While the species richness at the smaller sampling scales was similar to larger scales in the initial years following treatment (e.g., lower in herbicide treatment), a different pattern was observed by 2010 with burn and control quadrats having significantly lower species richness than herbicide and mechanical sites (Appendices B-10 and B-11). There were no differences in ground cover species evenness measures among treatments for any year ($p>0.05$) (Appendix B-12). Initially following treatments in 1996, average log abundance in the ground cover was significantly lower in herbicide sites than in burn and control sites ($p<0.05$), but this difference was absent after 1996 (Appendix B-13). By 2010, there were no differences in stem density for graminoids, forbs, or woody plants in the ground cover for any treatment ($p>0.05$). Graminoid stem density in the herbicide treatment was less

than that of control treatment in 1995 (p<0.05) and several species of grasses were no longer present by 2010 (Appendix B-14). Stem density of hardwood species in the ground cover was strongly reduced during the initial post-treatment sampling dates (1995-1998) in herbicide treatment sites only and tree stems remained marginally suppressed (p=0.08) relative to other treatments in 2010 (Appendix B-14). The multi-dimensional species diversity volume (Figure 26) illustrates how overall evenness, abundance and richness simultaneously changed in treatment and reference sites over time with the resulting composite metric showing an increase by 2010 for all treatments. In 1994 reference sites were easily distinguishable from the treatment sites, whereas, by 2010 reference and treatment sites are indistinguishable.

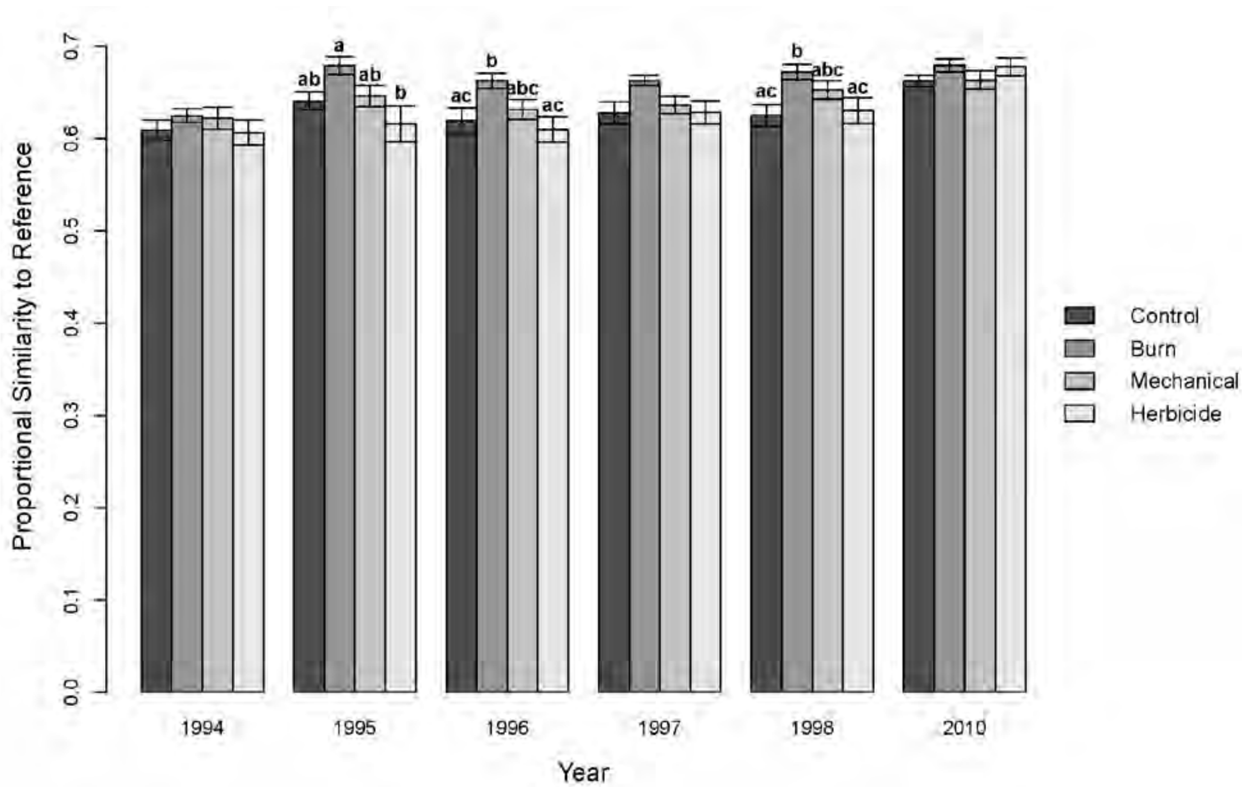


Figure 24. Means ±1 standard error (SE) of PS to reference conditions by treatment from 1994 to 2010 using log-transformed understory species abundance after removing rare species. Means with different letters are significantly different (Tukey's HSD, p < 0.05).

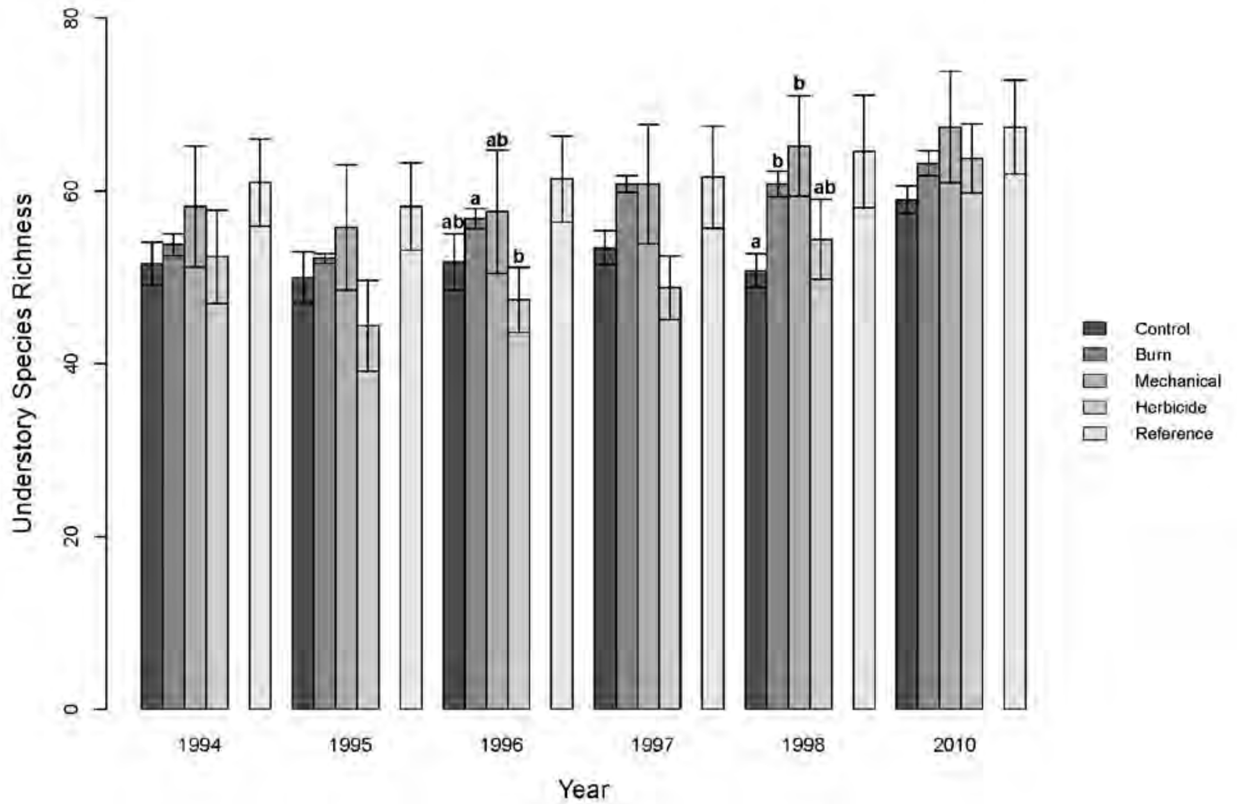


Figure 25. Mean ±1 SE of ground cover species richness at the treatment scale for treatment and reference sites from 1994 to 2010. Means with different letters are significantly different (Tukey's HSD, $p < 0.05$). Reference sites were not included in the ANCOVA and are shown only for visual comparison.

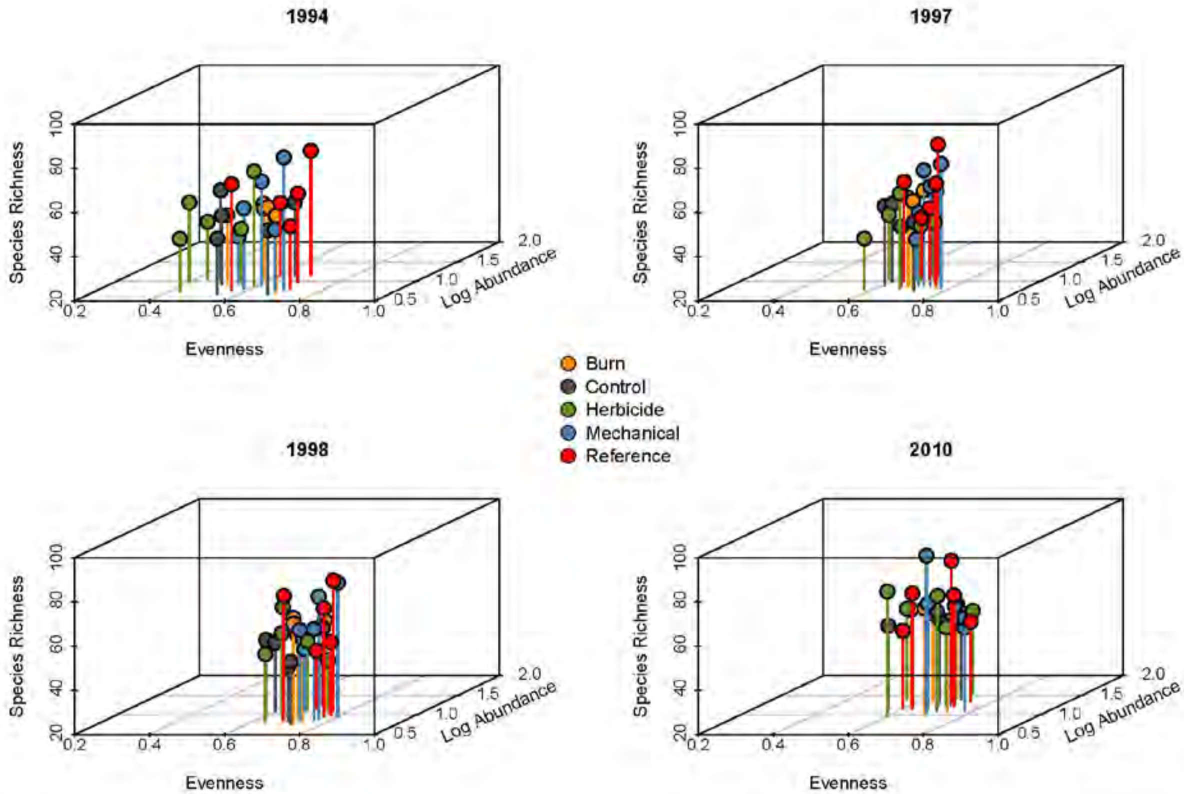


Figure 26. Multi-dimensional community diversity metrics (richness, evenness, average log abundance) by block for reference and treatment sites from 1994 to 2010.

By 2010, midstory deciduous oak density was greater in mechanical than herbicide treatments at the treatment scale ($p< 0.01$). By 2010, stem density of the evergreen oak, sand live oak (*Quercus geminata*) in the ground cover, was also greater in mechanical than herbicide treatments regardless of scale of measurement ($p<0.01$) (Appendix B-15). Interestingly, sand live oak density in the groundcover was consistently higher in reference sites as well, regardless of scale, although the density means were highly variable. Unfortunately, the initial experimental design precluded tests for statistical significance. More ruderal species were associated with the herbicide treatment by 2010 than other treatments ($p<0.01$) (Appendix B-16).

Reference condition indicator species

Twelve of the 15 ground cover species that were identified as indicators of reference sites in 1994 were not significant indicators of reference conditions by 2010, further reinforcing that treatment sites had become more similar to reference conditions over time (Appendix B-17). Most of these species increased in abundance as well as frequency of occurrence in treatment sites. Of particular interest among this group of species were wiregrass and anise scented goldenrod (*Solidago odora*), which have also been identified as species indicative of reference conditions in prior monitoring studies at Eglin, although wiregrass is generally restricted to the eastern part of the site (K. Hiers, personal communication). Both wiregrass and anise scented goldenrod were strongly correlated with the direction of change in ordination space ($p<0.001$). Of the eight species that were not indicators of reference conditions in 1994 but that became

indicators in 2010, rabbitbells (*Crotalaria rotundifolia*) and narrowleaf silkgrass (*Pityopsis graminifolia*) were also among those species previously identified as reference site indicators in previous monitoring studies (Hiers, pers. comm.). The three species that consistently represented reference sites over time were Carolina frostweed (*Helianthemum carolinianum*), pineland pinweed (*Lechea sessilifolia*), and eastern silver aster (*Symphyotrichum concolor*). Only pineland pinweed was strongly correlated with the direction of change in ordination space ($p<0.001$).

4.1.2 Treatment effects on fauna over time

Ordination

Fifty-eight species were included in analysis (Table 7). A two-dimensional solution was the best fit for the 1994 and 1998-1999 data with a final stress of 17.91 and an instability of 0.0005 after 200 iterations (stress was less than expected by chance; P = 0.03; Figure 27). Reference sites, located within the middle of Axis 1 in 1994, moved slightly along this axis between 1994 and 1998-1999. With one exception, control sites also moved slightly along Axis 1 between 1994 and 1998-1999 but were always separated from reference sites on Axis 2. All sites that experienced some form of hardwood removal in 1995 moved considerably along Axis 1 and approached references sites along Axis 2 (Figure 27).

Table 7. List of bird species included in ordination analyses

Common Name	Scientific Name
American Crow	*Corvus brachyrhynchos*
American Kestrel	*Falco sparverius*
Bachman's Sparrow	*Peucaea aestivalis*
Barn Swallow	*Hirundo rustica*
Blue-gray Gnatcatcher	*Polioptila caerulea*
Brown-headed Nuthatch	*Sitta pusilla*
Blue Grosbeak	*Passerina caerulea*
Blue Jay	*Cyanocitta cristata*
Brown Thrasher	*Toxostoma rufum*
Broad-winged Hawk	*Buteo platypterus*
Carolina Chickadee	*Poecile carolinensis*
Carolina Wren	*Thryothorus ludovicianus*
Cedar Waxwing	*Bombycilla cedrorum*
Chimney Swift	*Chaetura pelagica*
Common Ground Dove	*Columbina passerina*
Common Grackle	*Quiscalus quiscula*
Common Nighthawk	*Chordeiles minor*
Common Yellowthroat	*Geothlypis trichas*
Chuck-will's Widow	*Antrostomus carolinensis*
Downy Woodpecker	*Picoides pubescens*
Eastern Bluebird	*Sialia sialis*
Great Crested Flycatcher	*Myiarchus crinitus*
Great Horned Owl	*Bubo virginianus*
Hairy Woodpecker	*Picoides villosus*
Indigo Bunting	*Passerina cyanea*

Loggerhead Shrike	*Lanius ludovicianus*
Mississippi Kite	*Ictinia mississippiensis*
Mourning Dove	*Zenaida macroura*
Northern Bobwhite	*Colinus virginianus*
Northern Cardinal	*Cardinalis cardinalis*
Mockingbird	*Mimus polyglottos*
Orchard Oriole	*Icterus spurius*
Pine Warbler	*Setophaga pinus*
Pileated Woodpecker	*Dryocopus pileatus*
Purple Martin	*Progne subis*
Red-bellied Woodpecker	*Melanerpes carolinus*
Red-cockaded Woodpecker	*Picoides borealis*
Red-eyed Vireo	*Vireo olivaceus*
Red-headed Woodpecker	*Melanerpes erythrocephalus*
Red-shouldered Hawk	*Buteo lineatus*
Red-tailed Hawk	*Buteo jamaicensis*
Summer Tanager	*Piranga rubra*
Turkey Vulture	*Cathartes aura*
White-eyed Vireo	*Vireo griseus*
Wild Turkey	*Meleagris gallopavo*
Wood Thrush	*Hylocichla mustelina*
Yellow-billed Cuckoo	*Coccyzus americanus*
Yellow-shafted Flicker	*Colaptes auratus*

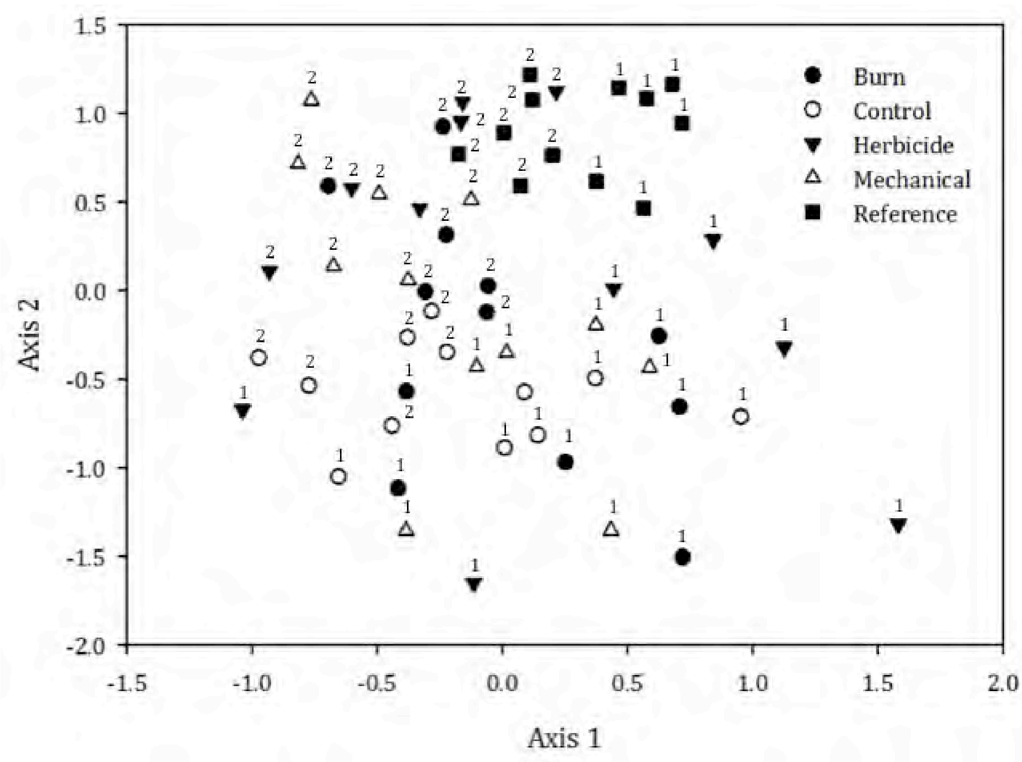


Figure 27. NMDS ordination of bird assemblages observed on fire-suppressed longleaf pine sandhills on Eglin AFB, pre-treatment (1) and early post-treatment (2).

A three-dimensional solution was the best fit for the 1998-1999 and 2009-2010 data with a final stress of 11.29 and an instability of 0.004 after 200 iterations (stress was less than expected by chance; P = 0.03; Figure 28). Control sites moved considerably along Axis 2. These sites displayed the greatest degree of change between 1998-1999 to 2009-2010, which was expected because the fire treatment they received was being initiated during this time while the other treatment sites were well into their restoration trajectories (i.e., they had not received a hardwood-removal treatment or prescribed burning by 1998-1999). There was considerable variation in the spatial arrangement of burn, mechanical, and herbicide sites but they appeared to be generally converging to the center of Axis 1 and the bottom of Axis 2.

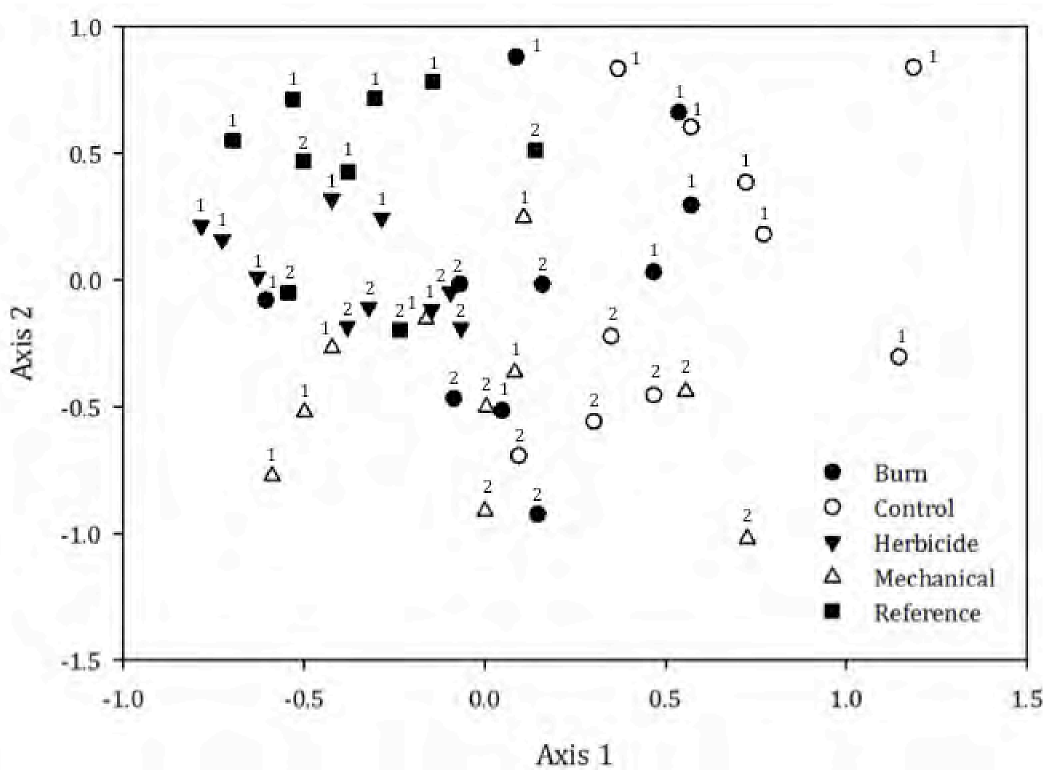


Figure 28. Non-metric dimensional scaling ordination of bird assemblages observed on longleaf pine sandhills following hardwood removal on Eglin AFB, early post-treatment (1) and late post-treatment (2). Axes 1 and 2 of the 3-D solution are presented.

Reference sites differed from treatment sites in 1994, whereas treatments were similar (Table 8). Following hardwood removal, control and reference sites were distinct from each other and all other treatment sites. In 2009-2010, reference sites were distinct from all treatments except herbicide sites, and herbicide sites differed from control and mechanical sites (Table 8).

Table 8. P-values associated with MRPP on pairwise comparisons of avian assemblages on treatment and reference sites. Bold indicates a significant difference between groups.

	Burn	Control	Mechanical	Herbicide	Reference
Pre-treatment					
Burn		0.55	0.94	0.85	**0.0006**
Control			0.86	0.21	**0.0006**
Mechanical				0.81	**0.0007**
Herbicide					**0.002**
Early Post-treatment					
Burn		**0.01**	0.10	0.25	**0.003**
Control			**0.0009**	**0.001**	**0.0005**
Mechanical				0.16	**0.0006**
Herbicide					**0.04**
Late Post-treatment					
Burn		0.36	0.54	0.05	**0.04**
Control			0.93	**0.02**	**0.01**
Mechanical				**0.01**	**0.01**
Herbicide					0.58

Identification of indicator species and occupancy modeling

Eight species were positively associated with reference sites in 1994; eight species were also positively associated with mechanical sites early post-treatment (Table 9). All other treatments had fewer, or no, indicator species (Table 9). Only two species were associated with the same treatment for both study periods following hardwood removal.

Table 9. Bird species identified as having a significant association with treatment or reference sites for all three study periods, Eglin AFB.

		Percent Indicator Value					
Treatment of Maximum Association	**Species**	**Burn**	**Control**	**Mechanical**	**Herbicide**	**Reference**	**P-value**
Pre-treatment							
Reference	American Kestrel	18	0	0	0	54	0.006
	Bachman's Sparrow	0	0	1	4	60	0.002
	Brown-headed Nuthatch	0	2	0	0	60	0.009
	Blue Grosbeak	2	8	11	5	51	0.003
	Blue Jay	14	23	17	17	29	0.007
	Northern Bobwhite	9	10	8	13	50	0.001
	Red-cockaded Woodpecker	7	1	3	4	60	0.001
	Red Headed Woodpecker	0	1	1	4	81	0.001
Control	Downy Woodpecker	6	43	16	3	2	0.016
	Northern Cardinal	19	35	23	10	2	0.047
	Pileated Woodpecker	17	34	8	17	4	0.048
Early Post-treatment							
Control	Eastern Titmouse	22	31	16	18	11	0.001
Mechanical	Blue Grosbeak	15	2	37	23	14	0.036
	Brown Thrasher	8	11	42	12	5	0.004
	Carolina Wren	19	20	36	12	1	0.043
	Chimney Swift	3	9	38	12	3	0.04
	Eastern Bluebird	6	1	41	35	5	0.023
	Eastern Towhee	13	6	48	5	0	0.008
	Indigo Bunting	6	0	50	2	0	0.01
	Summer Tanager	5	5	41	17	2	0.027
Reference	Red-cockaded Woodpecker	12	0	10	22	39	0.007
	Red Headed Woodpecker	24	0	20	16	37	0.004
Late Post-treatment							
Control	Eastern Titmouse	24	35	27	10	3	0.001
Mechanical	Eastern Towhee	27	28	37	2	3	0.018
Herbicide	Brown-headed Nuthatch	20	9	12	30	23	0.02
Reference	Mississippi Kite	0	0	0	0	67	0.022

For occupancy modeling, we selected six species that were positively associated with reference sites pre-treatment: American kestrel, Bachman's sparrow, blue grosbeak, brown-headed nuthatch, northern bobwhite and red-headed woodpecker (Table 10). Goodness of fit-tests for early post-treatment data did not provide evidence for any unexplained heterogeneity.

Occupancy of American kestrel and northern bobwhite in treatment sites was best explained by models that allowed occupancy to vary by primary sampling period. American kestrel occupancy was considerably lower in treatment sites than in reference sites pre-treatment, but these values were similar after hardwood removal (Table 11). Northern bobwhite occupancy remained relatively high throughout the duration of the study.

Estimated occupancy probabilities for Bachman's sparrow, brown-headed nuthatch, red-headed woodpecker, and blue grosbeak exhibited similar patterns through time (Figures 29-32). The most important models for each species included treatment as a covariate (Table 10). Occupancy probabilities for all four species were lower in treatment sites than in reference sites prior to hardwood removal. In general, occupancy probabilities for these species in mechanical and herbicide sites became similar to those in reference sites early post-treatment. By late post-treatment, however, occupancy probabilities in all treatment sites were similar to those in reference sites for all four species.

Table 10. Top models explaining occupancy patterns of select bird species within fire-suppressed longleaf pine sandhills undergoing hardwood removal, 1994-2010. PRD = primary sampling period, SURV = secondary sampling period, TRT = treatment, REF = reference.

Species	Site	Model	AIC	ΔAIC	Weight	Likelihood	P
American Kestrel	TRT	ψ(PRD),γ(PRD),p(TRT)	255.79	0	0.94	1.00	
	REF	ψ(.),γ(.),p(SURV)	103.08	0	0.90	1.00	
Blue Grosbeak							
	TRT	ψ,γ(TRT + PRD),ε(TRT + PRD),p(TRT + PRD)	468.64	0	0.46	1.0	
	TRT	ψ(PRD),γ(PRD),p(TRT + PRD)	469.15	0.51	0.36	0.77	
	REF	ψ(.),γ(.),p(SURV)	120.59	0	0.88	1.0	
Bachman's Sparrow							
	TRT	ψ,γ(TRT + PRD),ε(TRT + PRD),p(TRT + SURV)	339.23	0	0.97	1.00	
	REF	ψ(.),γ(.),p(SURV)	119.01	0	0.70	1.00	
		ψ(PRD),γ(PRD),p(SURV)	120.68	1.67	0.30	0.43	
Brown-headed Nuthatch							
	TRT	ψ,γ(TRT + PRD),ε(TRT + PRD),p(TRT + SURV)	294.13	0	0.79	1.00	
	REF	ψ(.),γ(.),p(.)	111.22	0	0.91	1.00	
Northern Bobwhite							
	TRT	ψ(PRD),γ(PRD),p(TRT + PRD)	544.44	0	0.97	1.00	
	REF	ψ(.),γ(.),p(.)	134.42	0	0.99	1.00	
Red-headed Woodpecker							
	TRT	ψ,γ(TRT),ε(TRT + PRD),p(TRT + PRD)	410.66	0	0.54	1.00	
	TRT	ψ,γ(TRT + PRD),ε(TRT + PRD),p(TRT + PRD)	410.98	0.32	0.46	0.85	
	REF	ψ(.),γ(.),p(.)	121.8	0	0.98	1.00	

Table 11. Probability of occupancy (and SE) for American kestrel and northern bobwhite observed on longleaf pine sandhills on Eglin AFB, 1994-2010.

	Pre-treatment	Early Post-treatment	Late Post-treatment
American Kestrel			
Treatment	0.18 (0.12)	0.85 (0.13)	0.7 (0.17)
Reference	0.83 (0.12)	0.83 (0.12)	0.83 (0.12)
Northern Bobwhite			
Treatment	0.99 (0.12)	0.97 (0.0)	1.0 (0.0)
Reference	1.0 (0.001)	1.0 (0.001)	1.0 (0.001)

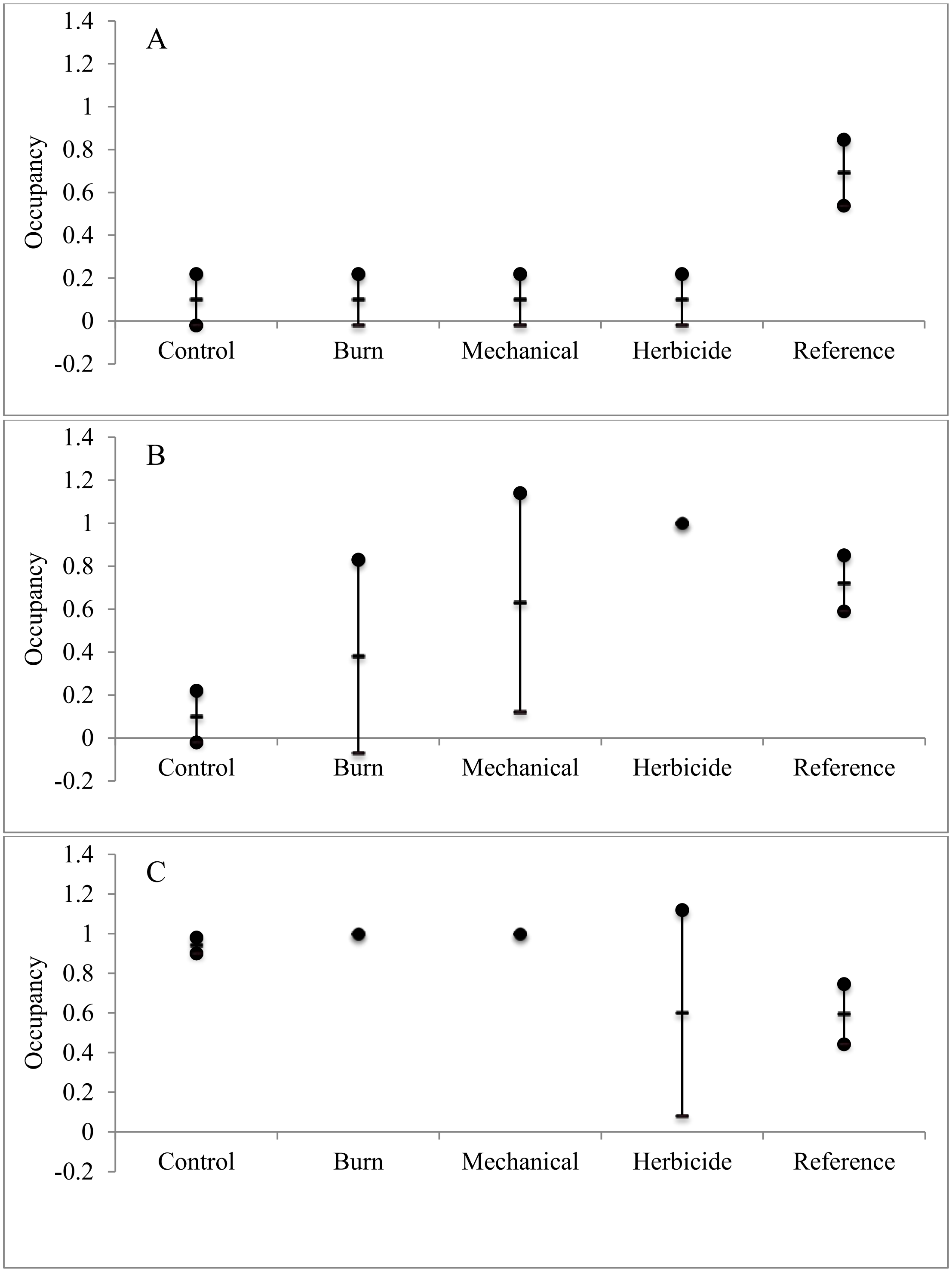


Figure 29. Relationship between probability of occupancy (and SE) and year of study for Bachman's sparrow pre-treatment (A), early post-treatment (B) and late post-treatment (C) following hardwood removal on fire-suppressed longleaf pine sandhills, Eglin AFB, Florida. Lack of numerical convergence and an inability to compute variance-covariance matrix suggest SE should be interpreted with caution.

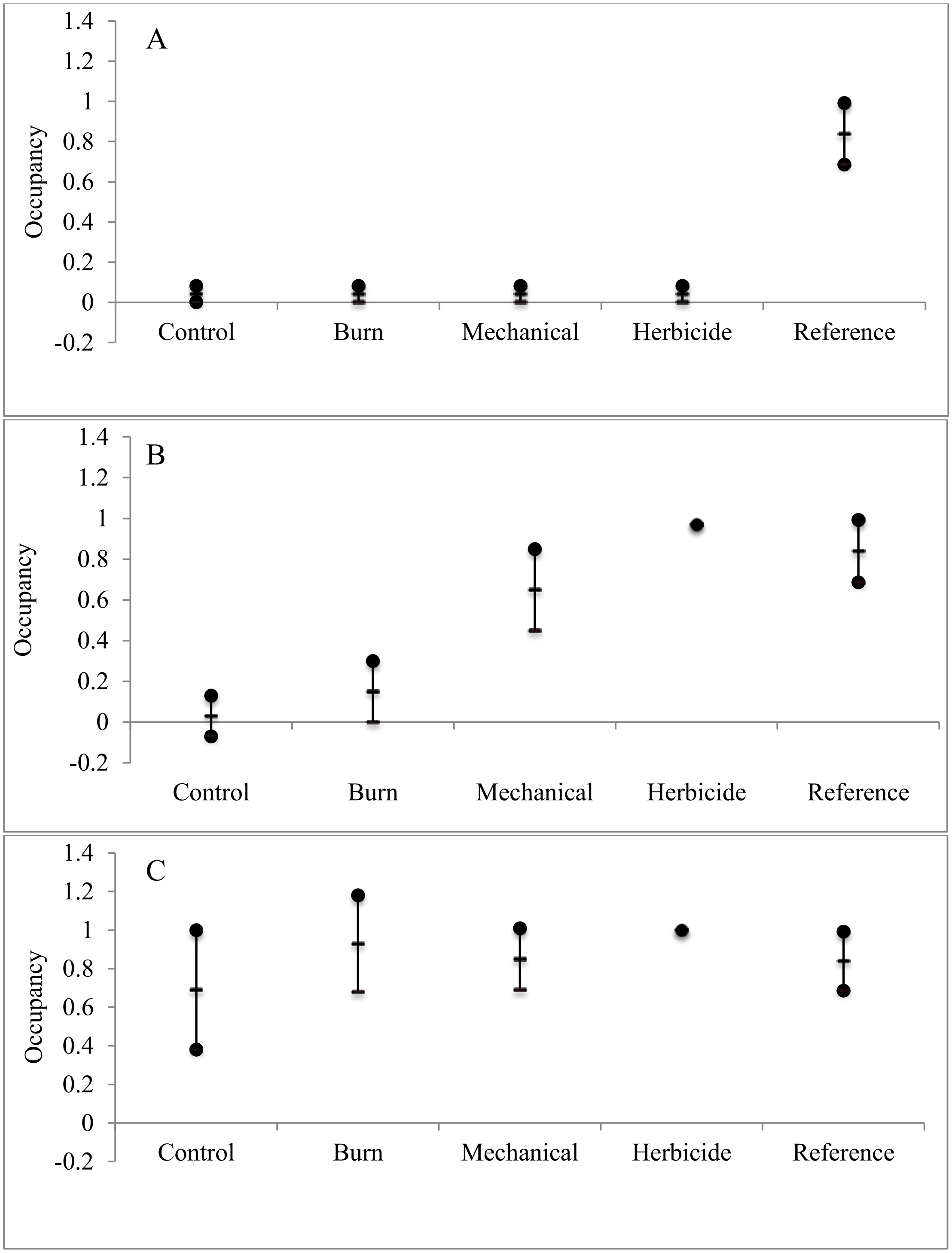


Figure 30. Relationship between probability of occupancy (and SE) and year of study for brown-headed nuthatch pre-treatment (A), early post-treatment (B) and late post-treatment (C) following hardwood removal on fire-suppressed longleaf pine sandhills, Eglin AFB, Florida. Program PRESENCE was unable to produce SE surrounding occupancy at Herbicide sites in B and C.

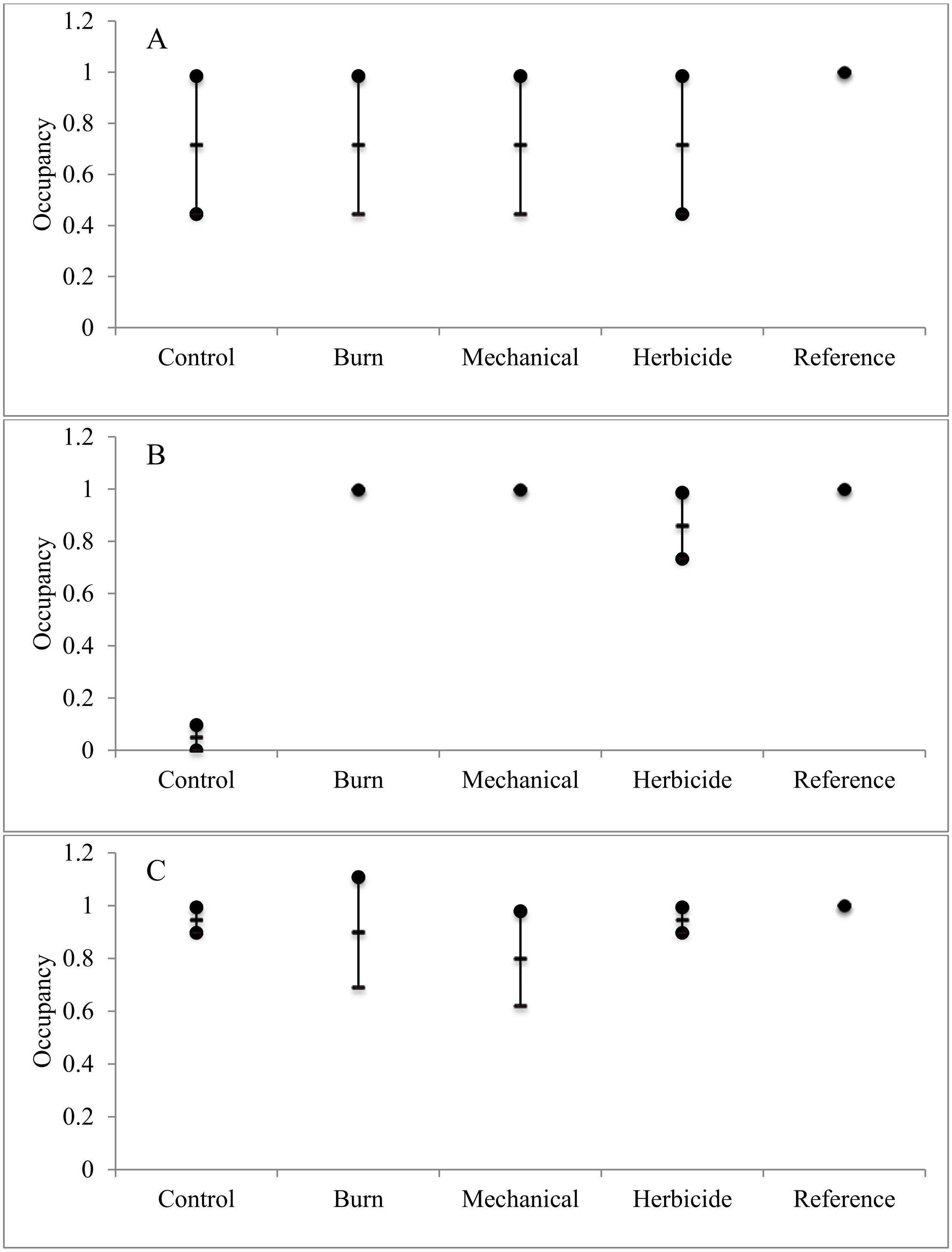


Figure 31. Relationship between probability of occupancy (and SE) and year of study for red-headed woodpecker pre-treatment (A), early post-treatment (B) and late post-treatment (C) following hardwood removal on fire-suppressed longleaf pine sandhills, Eglin AFB, Florida.

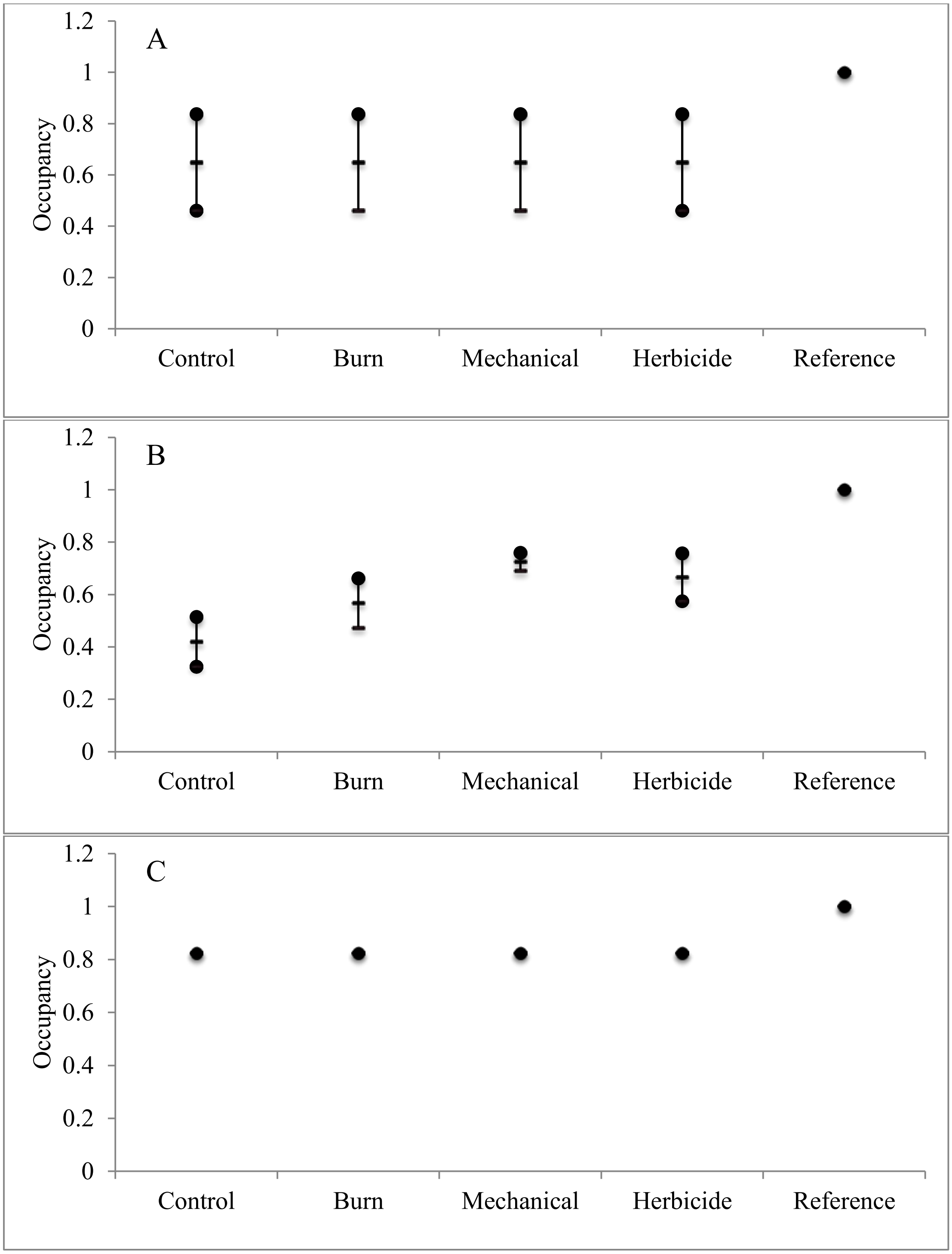


Figure 32. Relationship between probability of occupancy (and SE) and year of study for blue grosbeak pre-treatment (A), early post-treatment (B) and late post-treatment (C) following hardwood removal on fire-suppressed longleaf pine sandhills, Eglin AFB, Florida.

Reptile assemblage similarity

We recorded 1,775 captures of 16 reptile species early post-treatment and 1,648 captures of 19 reptile species late post-treatment (Table 12). Similarity (Morisita-Horn index) changed over time and differed between the hardwood removal treatments ($F_{4,1} = 2.20$, $P = 0.093$). Specifically, during the early post-treatment period, reference sites were more similar to each other than they were to herbicide ($P = 0.05$) and control sites ($P = 0.0006$). These trends are likely influenced heavily by two species; the relative proportion of six-lined racerunner was low in control and herbicide sites while the relative proportion of southeastern crowned snakes (*Tantilla coronata*) was higher in these sites (Figure 33).

Table 12. Total captures of reptiles by treatment and reference sites on Eglin AFB, 1997-1998 and 2009-2010. Trapping effort within a year increased in 2009-2010 and one reference site was excluded from study.

	Control	Burn	Herbicide	Mechanical	Reference	Total
Anolis carolinensis						
1997-1998	18	20	1	1	10	50
2009-2010	5	3	1	2	3	14
Aspidoscelis sexlineatus						
1997-1998	106	200	101	197	338	942
2009-2010	224	297	228	233	232	1214
Cemophora coccinea						
1997-1998	3	1	1	6	1	12
2009-2010	6	3	3	4	3	19
Coluber constrictor						
1997-1998	0	1	3	1	0	5
2009-2010	0	0	1	1	3	5
Coluber flagellum						
1997-1998	0	0	0	0	0	0
2009-2010	1	0	1	2	0	4
Diadophis punctatus						
1997-1998	3	0	0	0	0	3
2009-2010	0	0	0	0	0	0
Gopherus polyphemus						
1997-1998	0	0	0	0	0	0
2009-2010	0	0	0	0	1	1
Heterodon platyrhinos						
1997-1998	0	0	0	0	0	0
2009-2010	1	0	0	0	1	2
Lampropeltis elapsoides						
1997-1998	0	0	1	1	0	2
2009-2010	1	0	0	0	0	1
Micrurus fulvius						
1997-1998	0	0	1	0	0	1
2009-2010	0	0	0	0	0	0

Nerodia fasciata						
1997-1998	0	1	1	0	1	3
2009-2010	0	0	0	1	0	1
Plestiodon egregius						
1997-1998	7	8	2	2	4	23
2009-2010	3	5	1	4	4	17
Plestiodon laticeps						
1997-1998	22	6	11	10	3	52
2009-2010	8	14	7	4	4	37
Regina rigida						
1997-1998	0	0	0	0	0	0
2009-2010	0	1	0	0	0	1
Sceloporus undulatus						
1997-1998	13	50	16	29	30	138
2009-2010	42	56	28	26	49	201
Scincella lateralis						
1997-1998	29	22	10	18	15	94
2009-2010	10	9	4	3	8	34
Sistrurus miliarius						
1997-1998	2	1	0	1	0	4
2009-2010	2	0	1	1	1	5
Storeria occipitomaculata						
1997-1998	1	0	0	1	0	2
2009-2010	1	0	0	0	0	1
Tantilla coronata						
1997-1998	128	55	89	111	49	432
2009-2010	15	15	23	19	15	87
Terrapene carolina						
1997-1998	0	0	0	0	0	0
2009-2010	0	0	1	1	0	2
Virginia valeriae						
1997-1998	4	0	2	2	4	12
2009-2010	0	1	1	0	0	2

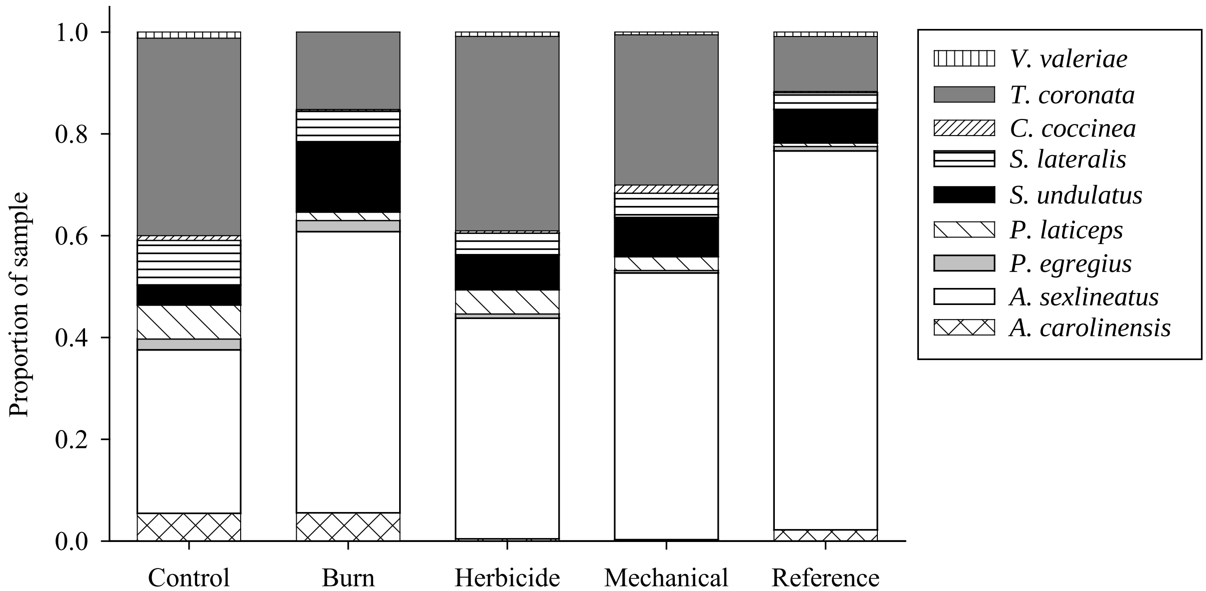


Figure 33. Relative proportion of species captured in treatment and reference sites on Eglin AFB, early post-treatment. Species captured ≤ 5 times are not included in figure.

Late post-treatment, similarity did not differ among treatments (Figure 34), similarity changed significantly at control (P = 0.0006) and herbicide (P = 0.06) sites between the two study periods. Cumulatively, this suggests that burn and mechanical treatments were effective at replicating the target condition shortly after treatment application (i.e., early post-treatment). Between this time period and late post-treatment, the reptile assemblages at control and herbicide sites changed significantly to become indistinguishable from those on reference sites.

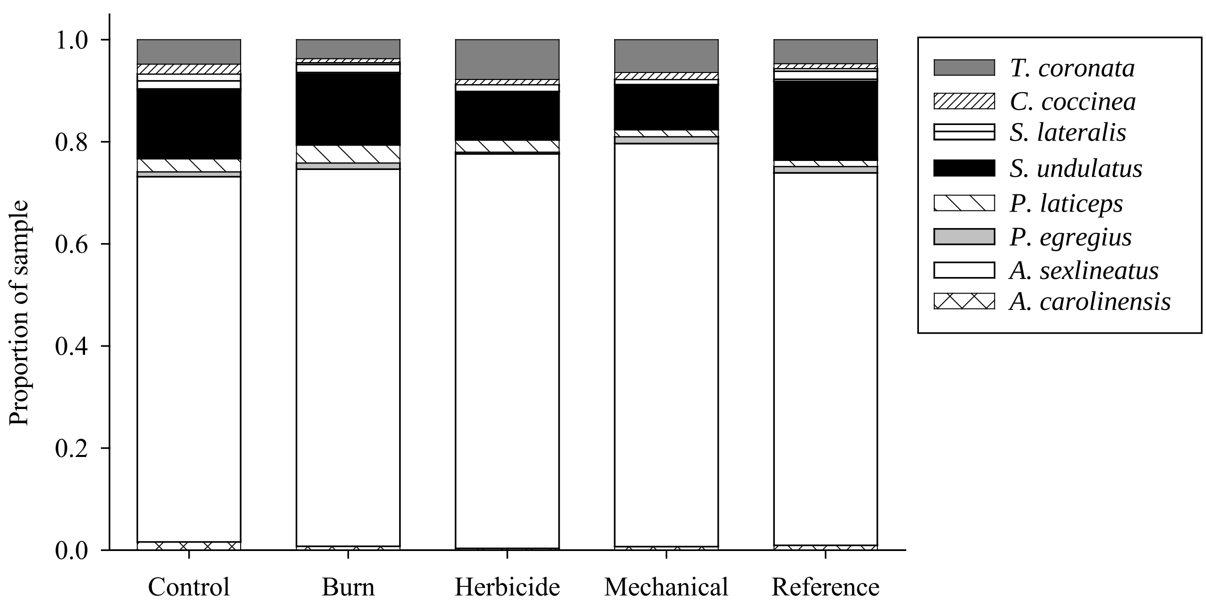


Figure 34. Relative proportion of species captured in treatment and reference sites on Eglin AFB, late post-treatment. Species captured ≤ 5 times are not included in figure.

NMDS

A two-dimensional solution best fit the data, with a final stress of 9.3 and instability of 0.00009 after 55 iterations. The stress was less than expected by chance (P = 0.03; Figure 35). Early post-treatment, control, mechanical, and herbicide sites were indistinguishable, based on the MRPP (Table 13). Reference sites were distinct from all treatments, as were burn sites. This suggests that mechanical and herbicide treatments did not alter the reptile assemblages such that they were different from assemblages at sites that experienced no hardwood removal. Reptile assemblages at burn sites likely represented an intermediate condition, different from those of control sites but still distinguishable from those of reference sites. Late post-treatment, reptile assemblages at herbicide sites were distinct from those of reference sites; otherwise there were no differences (Table 13).

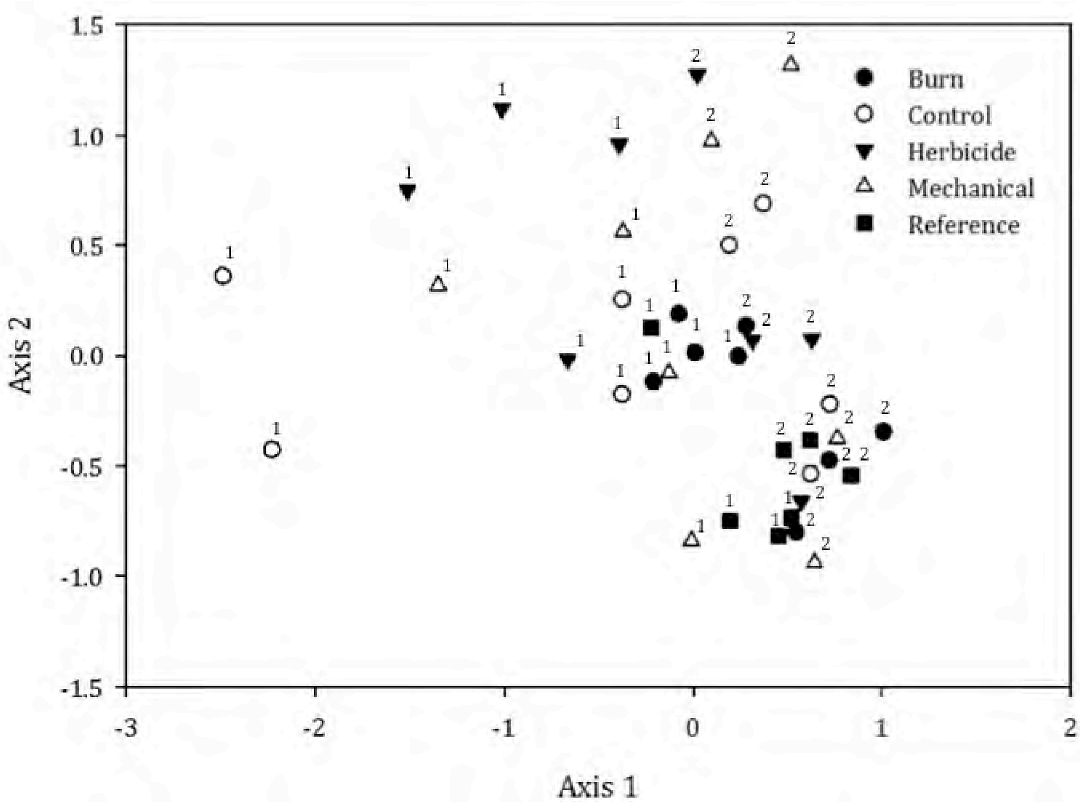


Figure 35. NMDS of treatment and Reference sites for early- and late post-treatment, Eglin AFB, Florida. 1 = early post-treatment, 2 = late post-treatment.

Table 13. P-values associated with MRPP on pairwise comparisons of reptile assemblages on treatment and reference sites (early- and late post-treatment). Bold indicates a significant difference between groups (α = 0.10).

	Burn	Control	Mechanical	Herbicide	Reference
Early post-treatment					
Burn	X	**0.01**	**0.008**	**0.01**	**0.034**
Control	X	X	0.46	0.24	**0.02**
Mechanical	X	X	X	0.3	**0.09**
Herbicide	X	X	X	X	**0.02**
Late post-treatment					
Burn	X	0.44	0.47	0.69	0.77
Control	X	X	0.53	0.77	0.19
Mechanical	X	X	X	0.9	0.19
Herbicide	X	X	X	X	**0.08**

Indicator species analysis

Three species were significantly associated with a particular treatment early post-treatment (Table 14). The six-line racerunner was positively associated with reference sites, ring-necked snake (*Diadophis punctatus*) was positively associated with control sites, and eastern fence lizard was positively associated with burn sites. No significant indicator species were identified in any of the treatments late post-treatment, indicating a relatively uniform distribution of species across treatments.

Table 14. Percent indicator values for reptile species significantly associated with a particular treatment on Eglin AFB, early post-treatment. Bold indicates a significant association with a particular treatment.

	Burn	Control	Mechanical	Herbicide	Reference	P-value
Aspidoscelis sexlineata	21	11	21	11	**36**	0.007
Diadophis punctatus	0	**75**	0	0	0	0.025
Sceloporus undulatus	**36**	9	21	12	22	0.015

CCA

For the early post-treatment data, 35.5% of the species distribution variance was explained by the first two axes (Figure 36). Eigenvalues for Axis 1 and 2 were significant (P = 0.03 and 0.09, respectively). Important habitat variables explaining variation on Axis 1 included fine litter (intraset correlation of -0.78). Species with CCA scores > 0.5 from 0 on this axis included scarlet snake (*Cemophora coccinea*; -0.53), and smooth earth snake (*Virginia valeriae*; -0.51). Important variables explaining variation on Axis 2 included oak midstory (intraset correlation of 0.67) and oak overstory (intraset correlation of 0.86). Species with scores > 0.5 from 0 on axis 2 included green anole (*Anolis carolinensis*; 0.55) and scarlet snake (-0.53). Eigenvalues for the late post-treatment data were not significantly different than expected by chance, suggesting variables did not explain variance in reptile abundance.

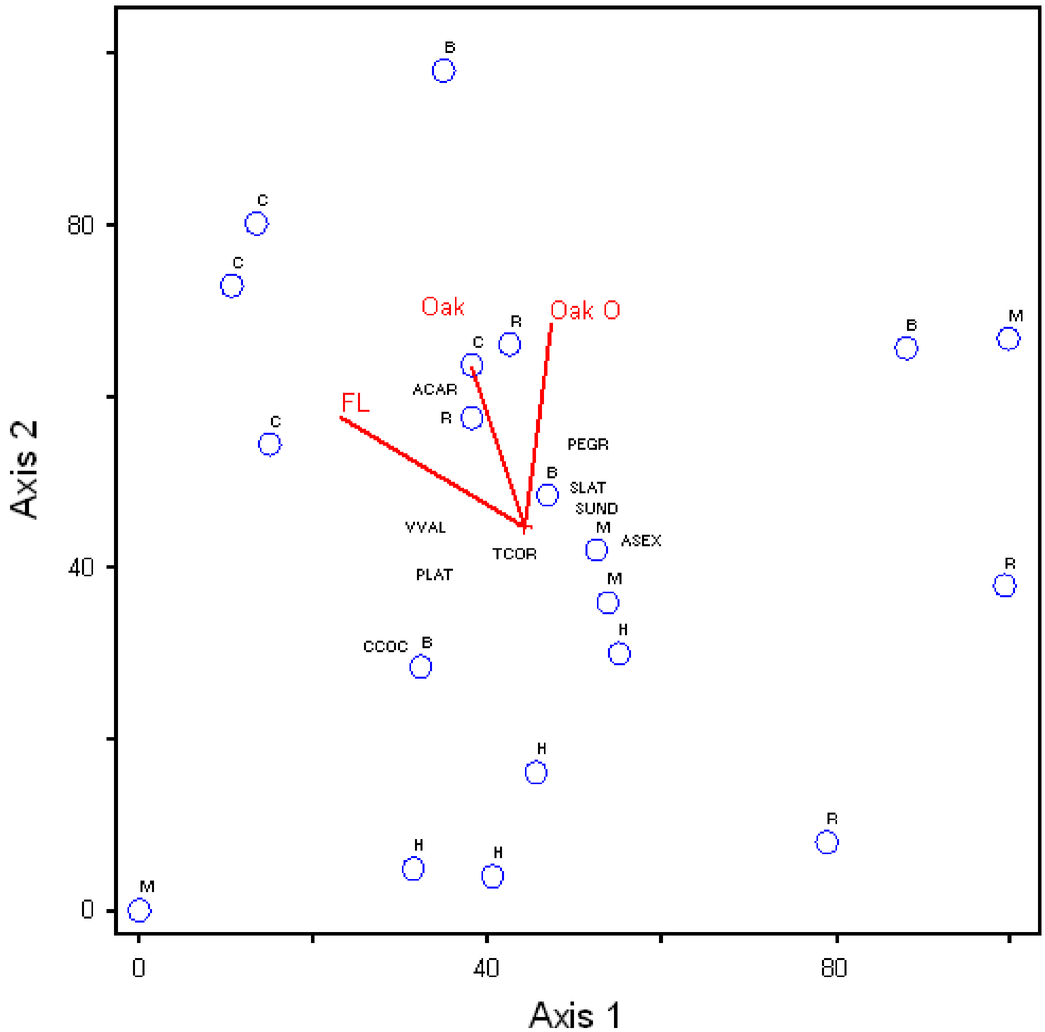


Figure 36. Canonical correspondence biplot for reptiles captured early post-treatment, Eglin AFB, Florida.

***Aspidoscelis sexlineata* mark-recapture**

We individually marked 521 and 773 six-lined racerunners in 1997-1998 and 2009-2010, respectively. There was no significant interaction between treatment and time ($F_{4,1} = 1.45$, $P = 0.24$) for the number of marked adults. In 1997-1998, the mean number of marked adults on reference sites (38, SE = 9.8) did not differ significantly from that of burn (23.25, SE = 1.5; P = 0.06) or mechanical sites (23.8, SE = 6.1; P = 0.06), but was greater than on control (13, SE = 4.7; P = 0.002) and herbicide sites (13.8, SE = 2.9; P = 0.003). In 2009-2010, the mean number of marked adults on reference sites (37, SE = 1.5) did not differ from that of burn (39.3, SE = 4.5; P = 0.76), control (29.8, SE = 3.9; P = 0.34), herbicide (32.5, SE = 4.9; P = 0.55) or mechanical sites (27.8, SE = 6.4; P = 0.22, Figure 37).

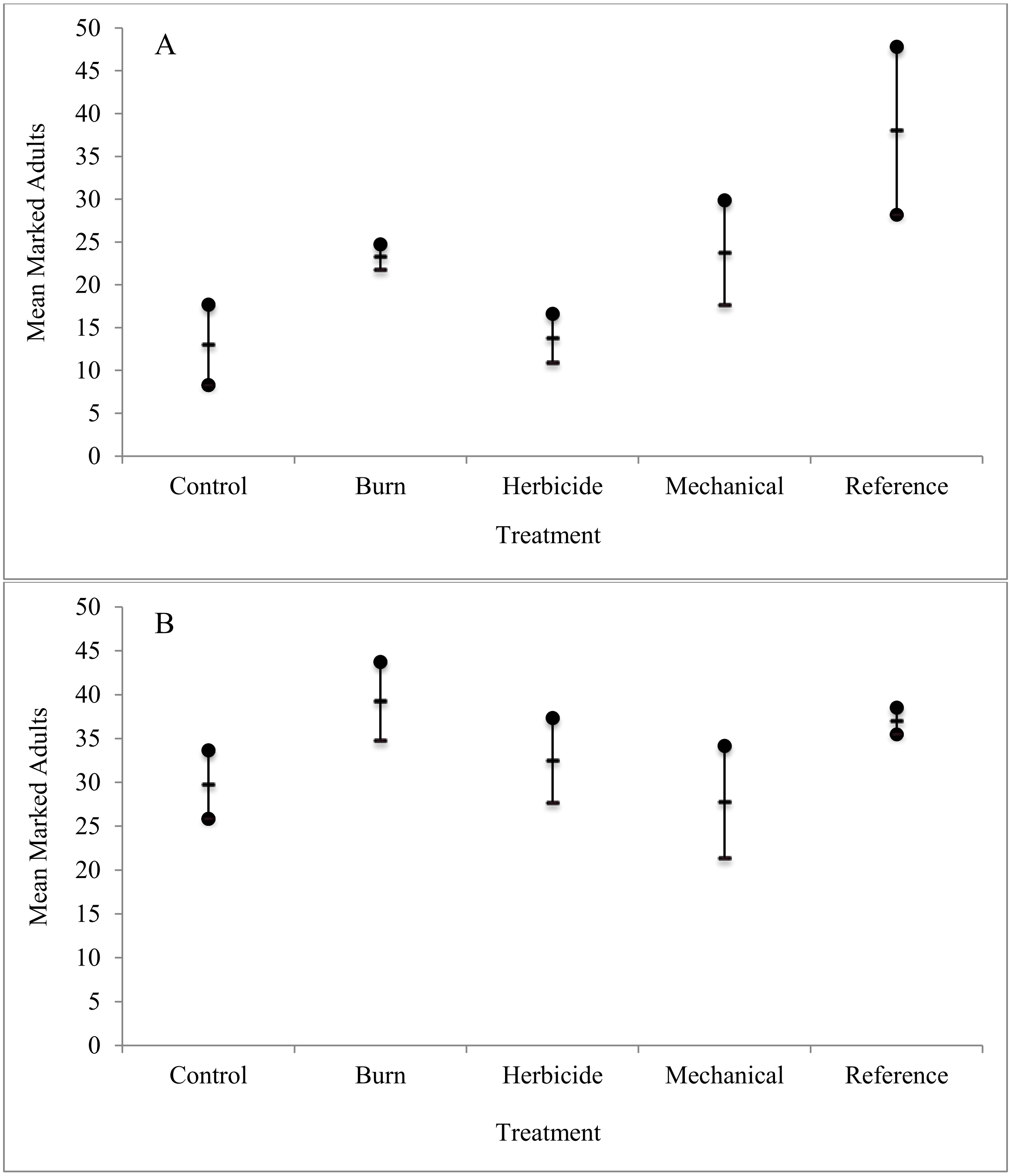


Figure 37. Mean number of marked adults (and SE) of six-lined racerunners in longleaf pine sandhills subjected to various hardwood removal strategies on Eglin AFB in 1997-1998 (A) and 2009-2010 (B).

With regard to the number of marked juveniles, there was no significant interaction between treatment and time ($F_{4,1} = 0.89$, $P = 0.49$). In 1997-1998, the mean number of marked juveniles on reference sites (10.3, SE = 0.9) was not significantly different than of burn (9.5, SE = 2.3; P = 0.80) or mechanical (5, SE = 1.2; P = 0.12) but was greater than that of control (2.3, SE = 1.1; P = 0.02) and herbicide sites (3.5, SE = 0.9; P = 0.046). In 2009-2010, the mean number of marked juveniles on reference sites(10, SE = 1.7) was not significantly different than

on burn (7.3, SE = 2.9; P = 0.41), control (5.8, SE = 2.5; P = 0.21), herbicide (5.8, SE = 2.1; P = 0.21), or mechanical (10, SE = 3.8; P = 1.0; Figure 38).

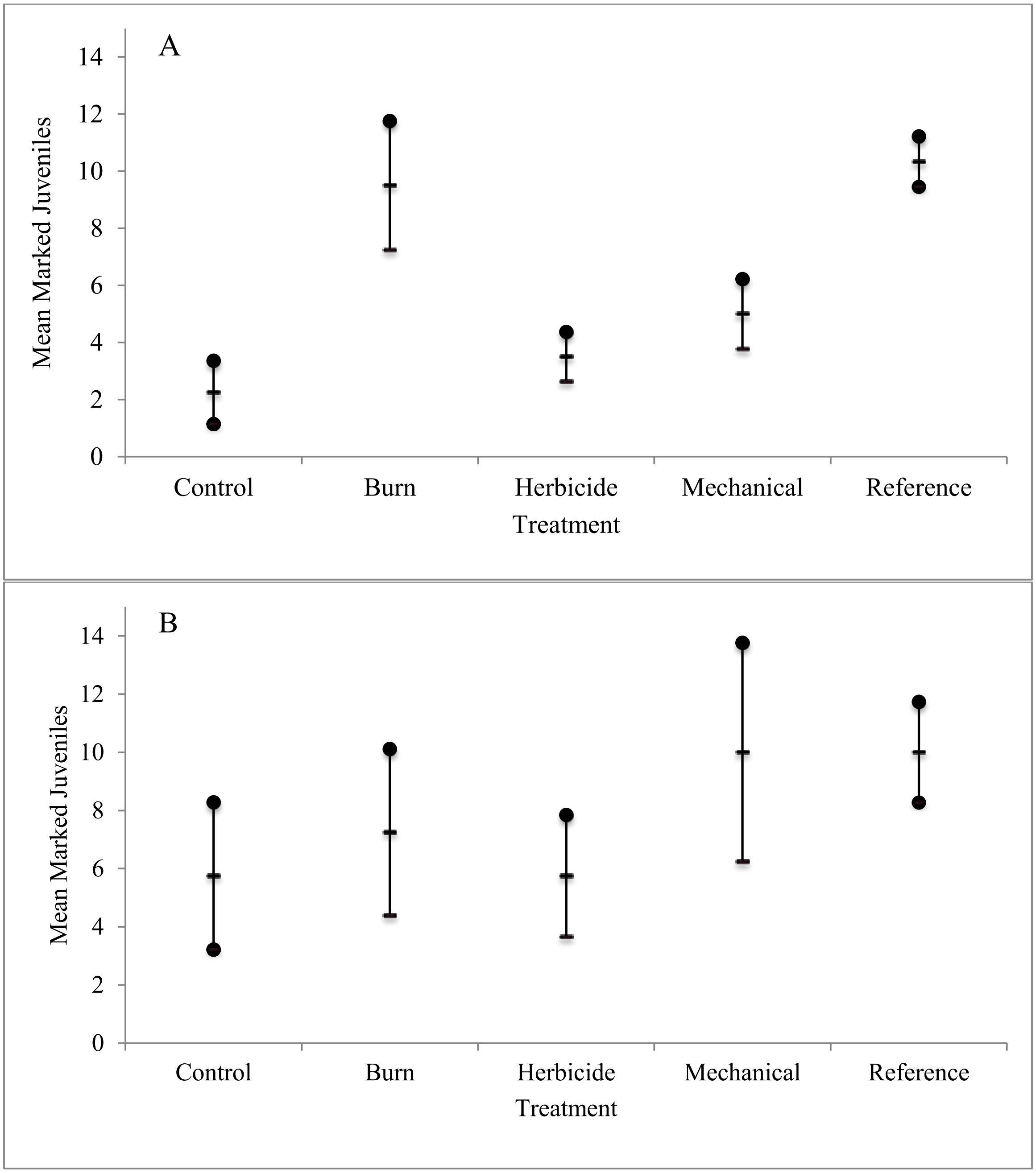


Figure 38. Mean number of marked juveniles (and SE) of six-lined racerunner in longleaf pine sandhills subjected to various hardwood removal strategies on Eglin AFB in 1997-1998 (A) and 2009-2010 (B).

In summary, the mean number of marked adults and juveniles on burn and mechanical sites was indistinguishable from the mean number of marked adults and juveniles on reference sites in 1997-1998 and the mean number of marked adults and juveniles on all treatments was indistinguishable from the mean number of marked adults and juveniles on reference sites in

2009-2010. Long-term prescribed burning influenced six-lined racerunner populations similarly on all sites, regardless of initial hardwood removal treatment. The numbers of adults and juveniles at Reference sites were relatively stable over time (Figures 37 and 38); because the numbers of adults and juveniles at control and herbicide sites were different than reference sites in 1998-1999 (while the numbers of these animals at mechanical and burn were not) and the numbers of these animals were the same in 2009-2010, we expected our before-after-control-impact ANOVA to return results suggesting significant change. We attribute the lack of significance to relatively small sample sizes and low detection probabilities; relatively high statistical power is required to detect interaction terms.

Small mammals

Unpredictable access to sites together with inclement weather that snapped traps confounded our ability to standardize sampling effort. In addition, low sample sizes precluded any statistical analyses. That said, we captured 59 individual mammals of four species in 2009 and 34 individual mammals of three species in 2010. Overall, we captured 72 oldfield mice (*Peromyscus polionotus*), 13 cotton mice (*Peromyscus gossypinus*), eight cotton rats (*Sigmodon hispidus*), and one North American least shrew (*Cryptotis parva*).

4.1.3 Treatment effects on soils

Pre-treatment, reference, burn-only, control, mechanical, and herbicide sites were all similar based on the MRPP analysis (Table 15). The first post-treatment analysis (spring 1996) showed that there were significant differences between the reference and all treatments (mechanical $P< 0.1$). In the second post-treatment analysis (spring 1997) the control sites differed from the burn-only, mechanical, herbicide ($P < 0.1$) and reference sites. The mechanical and herbicide ($P < 0.1$) also differed from the reference sites. In the spring 2009, we detected some differences between the treatments with the burn-only sites differing from the mechanical and herbicide sites, and the herbicide sites contrasting with the reference sites (Table 15).

Table 15. Results (P-values) associated with the MRPP on pairwise comparisons of soil total C, total N, and CN ratios on restoration treatments and reference sites for pre-treatment (fall of 1994) and post-treatment. N.S. = not significant.

Treatment	Reference	Burn-only	Delayed burn	Herbicide	Mechanical
Pre-treatment (Fall 1994)					
Reference		N.S.	N.S.	N.S.	N.S.
Burn-only			N.S.	N.S.	N.S.
Delayed burn				N.S.	N.S.
Herbicide					N.S.
Early Post-treatment (Spring 1996)					
Reference		0.003	0.04	0.001	N.S.
Burn-only			N.S.	N.S.	N.S.
Delayed burn				N.S.	N.S.
Herbicide					0.099
Early Post-treatment (Spring 1997)					
Reference		N.S.	0.001	0.066	0.001
Burn-only			0.046	N.S.	N.S.
Delayed burn				N.S.	0.046
Herbicide					N.S.
Late Post-treatment (Spring 2009)					
Reference		N.S.	N.S.	0.04	N.S.
Burn-only			N.S.	0.035	0.04
Delayed burn				N.S.	N.S.
Herbicide					N.S.

In the initial (1994-1997) study, pH showed very little variability with no differences between years (4.64 to 4.71; $P = 0.5237$) or treatments (4.64 to 4.81; $P = 0.8623$) for the 0-30 cm layer, despite dramatic changes in vegetative cover within the initial treatments (Provencher et al., 2001a, Provencher et al. 2001b). In the 2009 post-treatment sampling, soil pH was slightly more basic than the initial study and pH and bulk density differed with depth (Tables 16, 17). Soil pH showed low variability, with ranges of 4.8-5.4 and 5.1-5.4 respectively for the 0-10 cm and 10-30 cm layer of the mineral soil. In contrast, soil bulk density was more variable with ranges from 0.007 to 0.06 g cm^{-3} for the litter layer and from 0.7 to 1.4 g cm^{-3} for the two mineral soil horizons. Soil pH was slightly more acidic in the 0-10 cm (5.04) than the 10-30 cm (5.17) layers while soil bulk density was lower in the litter layer (Tables 16, 17).

Table 16. Results of a GLMM testing the effect of treatment, depth and interaction treatment × depth on soil pH, soil bulk density, melich P, and soil C and N pools and mineralization rates for the 2009 post-treatment. P-values and degrees of freedom were produced with Wald χ2 tests. The reference treatment was not included in the GLMM testing. N.S. = not significant. W = weight; V = volume.

Effects	**df**	**Bulk density**	**C_w**	**N_w**	**C:N ratio**	**C_v**	**N_v**
Treatment	3	N.S.	N.S.	0.0339	<0.0001	N.S.	N.S.
Depth	2	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
T × D	6	N.S.	N.S.	<0.0001	0.0023	N.S.	0.0554
		$NO_3^-{}_w$	**$NO_3^-{}_v$**	**$NH_4^+{}_w$**	**$NH_4^+{}_v$**	**N nit_w**	**N nit_v**
Treatment	3	0.0200	0.0145	0.0022	0.0024	0.0009	0.0070
Depth	1	N.S.	<0.0001	<0.0001	<0.0001	N.S.	N.S.
T × D	3	N.S.	N.S.	0.0188	N.S.	N.S.	N.S.
		Net N min_w	**Net N min_v**	**P_w**	**P_v**	**pH**	**Moisture**
Treatment	3	N.S.	N.S.	0.0152	N.S.	N.S.	N.S.
Depth	1	0.0017	0.0065	<0.0001	0.0350	<0.0001	N.S.
T × D	3	N.S.	N.S.	0.0283	N.S.	N.S.	N.S.

Table 17. Means and SE of soil characteristics for reference (not included in the GLMM testing) and treatment sites in longleaf pine forests at Eglin AFB, Florida for summer 2009. Means for treatment or depth with the same letter do not differ at P < 0.05. NM = not measured.

	Reference	Burn-only	Delayed burn	Herbicide	Mechanical
Bulk Density (g cm^{-3})					
Litter a	0.031 (0.003)	0.037 (0.006) a	0.028 (0.001) a	0.022 (0.005) a	0.027 (0.002) a
Min 0–10 cm b	0.98 (0.07)	0.94 (0.04) a	1.01 (0.05) a	1.07 (0.05) a	1.03 (0.04) a
Min 10–30 cm c	1.15 (0.09)	1.18 (0.06) a	1.20 (0.03) a	1.26 (0.04) a	1.22 (0.03) a
pH					
Litter	NM	NM	NM	NM	NM
Min 0–10 cm a	5.03 (0.05)	4.98 (0.06) a	5.10 (0.08) a	5.06 (0.07) a	5.05 (0.03) a
Min 10–30 cm b	5.21 (0.05)	5.15 (0.02) a	5.13 (0.03) a	5.18 (0.02) a	5.19 (0.05) a
C (%)					
Litter a	51.12 (0.90)	50.21 (0.64) a	49.73 (0.58) a	50.28 (1.13) a	50.03 (0.37) a
Min 0–10 cm b	1.23 (0.17)	1.27 (0.09) a	1.06 (0.10) a	0.97 (0.05) a	0.96 (0.03) a
Min 10–30 cm c	0.45 (0.03)	0.52 (0.04) a	0.53 (0.05) a	0.46 (0.02) a	0.48 (0.02) a
N (%)					
Litter a	0.57 (0.03)	0.60 (0.05) b	0.72 (0.04) a	0.70 (0.01) a	0.64 (0.02) ab
Min 0–10 cm b	0.046 (0.007)	0.047 (0.003) a	0.045 (0.003) a	0.042 (0.002) a	0.038 (0.002) a
Min 10–30 cm c	0.019 (0.001)	0.021 (0.002) a	0.022 (0.001) a	0.022 (0.002) a	0.020 (0.001) a
CN ratio					
Litter a	95.3 (3.1)	87.3 (6.2) a	69.9 (6.4) c	73.6 (1.5) bc	80.9 (1.8) ab
Min 0–10 cm b	27.8 (0.7)	26.9 (1.4) a	23.6 (0.5) a	23.2 (0.6) a	25.8 (0.7) a
Min 10–30 cm b	24.0 (0.7)	24.5 (1.0) a	23.6 (0.8) a	21.1 (0.3) a	23.7 (0.8) a
C pool (g m^{-2})					
Litter a	158.7 (17.4)	187.4 (31.6) a	140.6 (6.4) a	108.3 (22.9) a	135.4 (9.5) a
Min 0–10 cm b	1139.7 (71.4)	1209.7 (63.0) a	1055.2 (87.0) a	1013.6 (53.0) a	972.7 (43.2) a
Min 10–30 cm b	1032.5 (103.0)	1194.0 (69.4) a	1276.0 (128.6) a	1151.4 (78.5) a	1162.8 (59.9) a
N pool (g m^{-2})					
Litter a	1.96 (0.24) a	2.28 (0.43) a	2.13 (0.16) a	1.52 (0.32) a	1.80 (0.17) a
Min 0–10 cm c	39.5 (1.96) a	45.2 (2.82) a	44.7 (3.31) a	43.5 (1.67) a	38.1 (2.40) a
Min 10–30 cm b	43.3 (4.42) b	47.6 (2.60) a	53.7 (3.75) a	56.3 (4.46) a	49.4 (2.60) a
Moisture (%)					
Litter	NM	NM	NM	NM	NM
Min 0–10 cm a	0.02 (0.01)	0.07 (0.05) a	0.03 (0.04) a	0.05 (0.02) a	0.03 (0.01) a
Min 10–30 cm a	0.03 (0.01)	0.05 (0.01) a	0.04 (0.01) a	0.03 (0.01) a	0.04 (0.01) a

In the initial sampling effort (1994-1997), bulk soil carbon concentration was significantly lower during spring 1997 than fall 1994 and spring 1996 ($P< 0.0001$) with no treatment effect ($P = 0.1885$) on C concentration (Figure 39). Nitrogen (%) also showed some variability between the years with differences between 1997 (spring and fall), and fall 1994 and spring 1996 ($P < 0.0001$), with also no treatment effect ($P = 0.3407$; Figure 39). CN ratios were higher during fall 1997 than spring 1997 ($P < 0.0001$), and similar to C and N, restoration treatments had no significant effect *(P*= 0.2626; Figure 39). As for the 2009 sampling (when 0-10 and 10-30 cm layers were combined), the effects of treatment were statistically significant for CN ratios ($P= 0.0013$) and only marginally significant for soil C ($P= 0.0710$), with lower values in the herbicide than the burn-only sites (Figure 39).

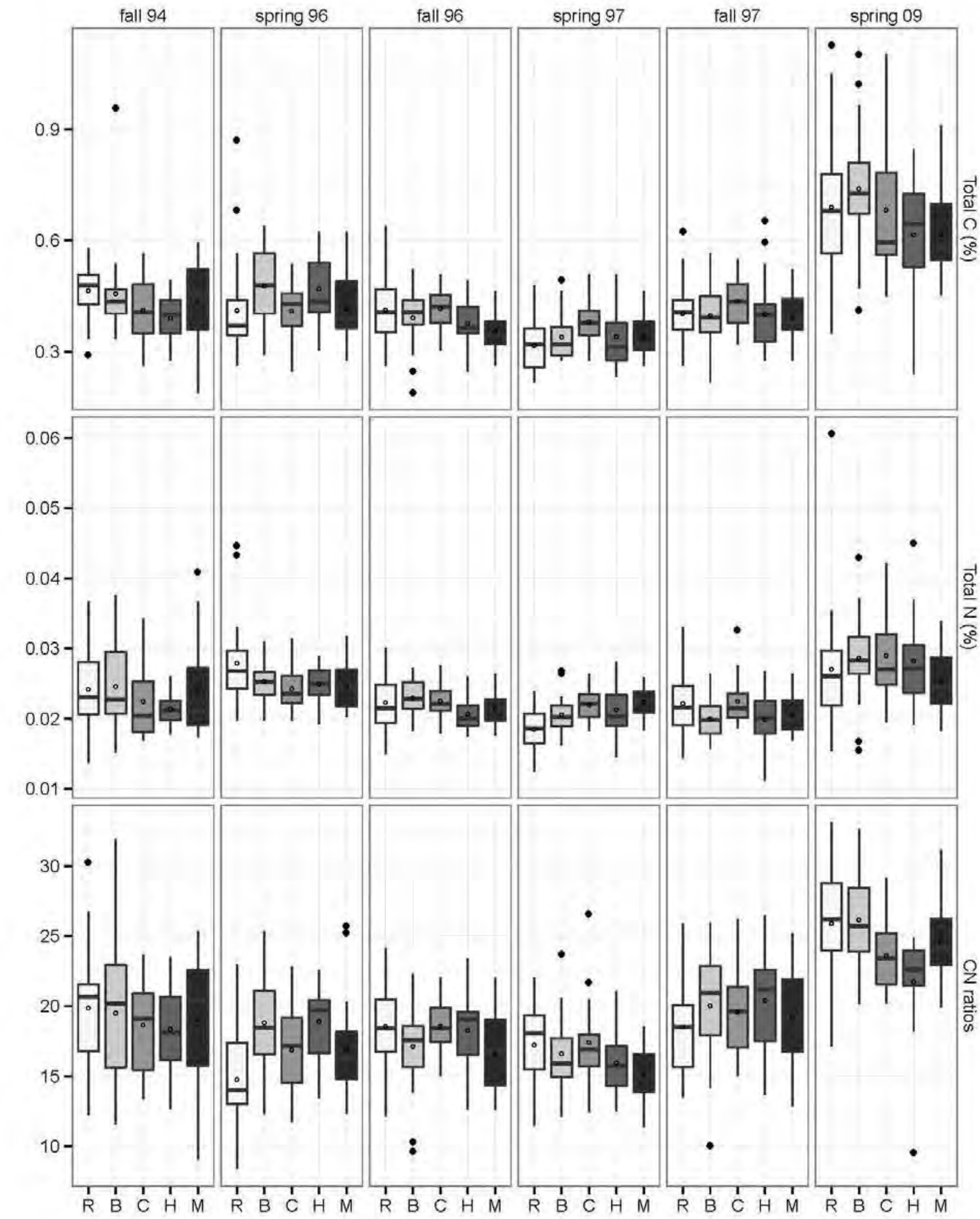


Figure 39. Box plots of soil total C (%), total N (%), and CN ratios for longleaf pine forests at Eglin AFB, Florida. The boundary of the box plot closest to zero indicates the 25th percentile, the line within the box marks the median, and the boundary of the box plot farthest from zero indicates the 75th percentile. Error bars above and below indicate the 90th and 10th percentile.

Means (open circles) for treatments (Reference not included in the GLMM analysis) with the same letter do not differ at $P < 0.05$. R=reference; B=burn-only; C=control; H=herbicide; M=mechanical.

In the 2009 post-treatment sampling we also measured three soil horizons, the litter, and the 0-10 cm and 10-30 cm mineral layers. These three layers were combined in the initial study. In the 2009 post-treatment sampling, treatment and depth interacted significantly only for total N and CN ratios (Table 16). Concentrations of C and N and CN ratios were significantly higher in the litter layer than the mineral soil horizons while the opposite was observed for C and N pools (Tables 16, 17). The effect of treatment was more variable and specific to each soil layer (Table 17). We failed to detect significances for C (% and pool), whereas our results were slightly different for N (%); for the litter layer, total N (%) was higher in the control and herbicide than the burn-only sites; for the 0-10 cm and 10-30 cm we did not measure any difference between the treatments (Table 17). In addition, the effect of treatment on the CN ratio for the litter layer was higher in the burn-only than the control and herbicide sites (Table 17).

We also compared the C and N pools of the 2007 post-treatment sampling with the 2009 post-treatment sampling (0-30 cm; Figure 40). We did not detect any significant interaction effect for C ($P=0.6674$) or N ($P=0.2319$) pools. Similarly, our study also showed no difference between restoration sites for C ($P=0.1595$) and N ($P=0.4448$). Thus, these results suggest that the difference in C or N pools among the treatments (excluding the reference) did not change between the two studies.

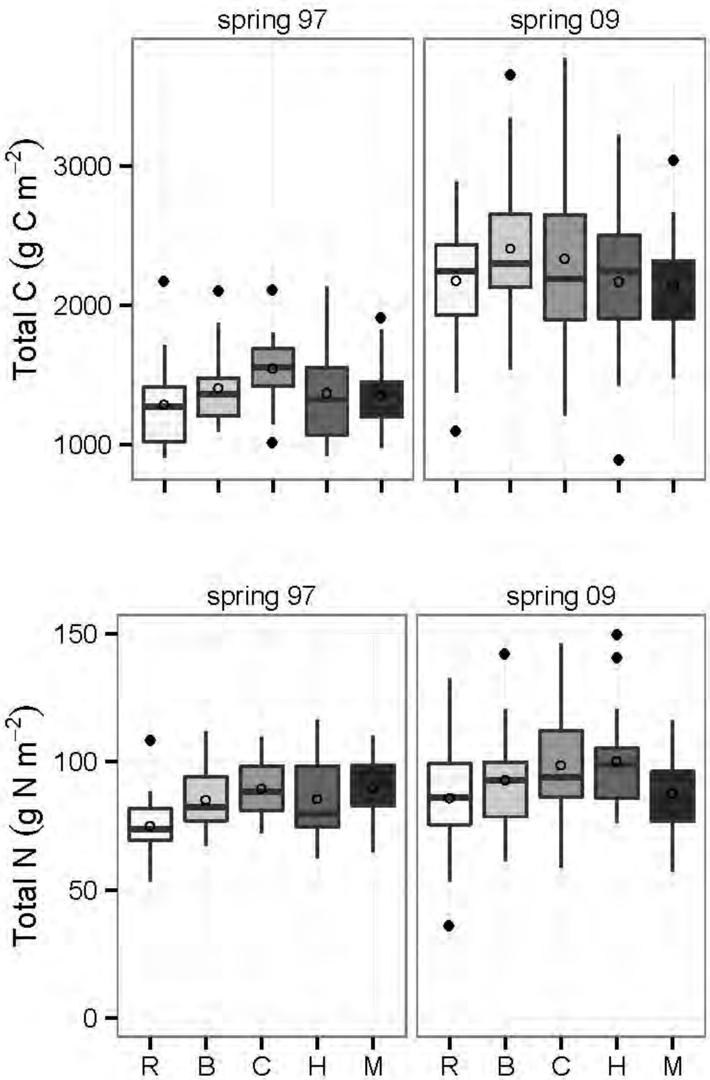


Figure 40. Box plots of C and N pools (0-30 cm mineral soil layer) for longleaf pine forests at Eglin AFB. The boundary of the box plot closest to zero indicates the 25th percentile, the line within the box marks the median, and the boundary of the box plot farthest from zero indicates the 75th percentile. Error bars above and below indicate the 90th and 10th percentile. Means (open circles) for treatments (Reference not included in the GLMM analysis) with the same letter do not differ at $P < 0.05$. R=reference; B=burn-only; C=control; H=herbicide; M=mechanical.

Extractable NO_3^- and NH_4^+ concentrations and pools and nitrification rates were generally low in all sites and expressed more variability than C and N. NH_4^+ on a dry soil mass basis showed a significant interaction between treatment and depth, with concentrations of NH_4^+ highest in the 0-10-cm layer of control sites (Tables 16, 18). We detected a significant treatment effect for NO_3^- and NH_4^+ concentrations and pools and nitrification rates; and depth effect for NH_4^+ concentrations and pools, and N min rates (Table 16).

Table 18. Means and SE of inorganic N and N mineralization, and P for reference (not included in the GLMM testing) and restoration sites in longleaf pine forests at Eglin AFB for summer 2009. Means for treatment and depth with the same letter (capital letter was used when the two soil horizons were combined) do not differ at $p < 0.05$.

	Reference	Burn-only	Delayed burn	Herbicide	Mechanical
NH_4 (µg NH_4 gdw^{-1})					
Min 0–10 cm a	1.14 (0.19)	1.64 (0.16) b	2.60 (0.45) a	1.81 (0.31) b	1.48 (0.17) b
Min 10–30 cm b	0.91 (0.07)	1.08 (0.12) a	1.29 (0.13) a	1.27 (0.16) a	0.97 (0.09) a
NO_3 (µg NO_3 gdw^{-1})					
Min 0–10 cm a	0.12 (0.05)	0.25 (0.06) B	0.22 (0.06) B	0.41 (0.10) A	0.25 (0.08) B
Min 10–30 cm a	0.15 (0.01)	0.32 (0.08)	0.31 (0.08)	0.36 (0.12)	0.24 (0.05)
NH_4 (g NH_4 m^{-2})					
Min 0–10 cm a	0.12 (0.02)	0.15 (0.02) B	0.27 (0.05) A	0.19 (0.04) AB	0.15 (0.02) B
Min 10–30 cm b	0.22 (0.03)	0.24 (0.02)	0.32 (0.04)	0.32 (0.04)	0.24 (0.02)
NO_3 (g NO_3 m^{-2})					
Min 0–10 cm a	0.012 (0.004)	0.022 (0.006) B	0.022 (0.008) B	0.045 (0.011) A	0.026 (0.008) B
Min 10–30 cm b	0.036 (0.005)	0.075 (0.022)	0.075 (0.022)	0.102 (0.029)	0.059 (0.012)
Nitrification (µg NO_3 $kg^{-1}d^{-1}$)					
Min 0–10 cm a	9.67 (3.64)	8.80 (8.63) AB	18.98 (12.22) A	−7.66 (7.96) B	4.47 (5.10) B
Min 10–30 cm a	13.92 (4.62)	5.24 (6.65)	18.23 (14.06)	−2.66 (5.96)	−2.03 (2.77)
N min (µg N min $kg^{-1}d^{-1}$)					
Min 0–10 cm a	16.95 (6.02)	10.22 (9.65) a	9.97 (6.72)a	5.59 (7.54) a	10.84 (7.64) a
Min 10–30 cm b	−3.19 (7.23)	−5.42 (7.10) a	3.47 (14.43)a	−13.87 (11.70)a	−13.57 (3.39) a
Nitrification (mg NO_3 $m^{-2}d^{-1}$)					
Min 0–10 cm a	0.97 (0.41)	0.83 (0.82)AB	1.68 (1.21) A	−0.85 (0.83) B	0.49 (0.49) B
Min 10–30 cm a	2.92 (7.18)	0.76 (1.67)	4.30 (3.31)	−0.73 (1.43)	−0.53 (0.70)
N min (mg N min $m^{-2}d^{-1}$)					
Min 0–10 cm a	1.60 (0.64)	0.81 (0.82) a	0.92 (0.65) a	0.33 (0.75) a	1.04 (0.78) a
Min 10–30 cm b	−1.29	−1.58	0.73 (3.44)	–3.40	−3.39 (0.82)

	(1.43)	(1.89) a	a	(1.25) a	a
P (µg gdw^{-1})					
Min 0–10 cm a	0.89 (0.12)	0.68 (0.08) b	1.26 (0.34) a	0.68 (0.04) b	0.73 (0.05) b
Min 10–30 cm b	0.34 (0.03)	0.38 (0.05)a	0.48 (0.08) a	0.41 (0.07) a	0.37 (0.05) a
P (g m^{-2})					
Min 0–10 cm a	0.088 (0.013)	0.067 (0.008) a	0.131 (0.043) a	0.075 (0.009) a	0.075 (0.062) a
Min 10–30 cm b	0.084 (0.008)	0.109 (0.021) a	0.121 (0.018) a	0.129 (0.039) a	0.090 (0.011) a

Ammonium (volume basis) was higher in the control than the burn-only, and mechanical treatments while NO_3^- (dry soil mass and volume basis) was highest in the herbicide sites (Table 18). We also measured significantly lower nitrification rates in the herbicide sites (Table 18).

Concentrations and pools of melich P ranged from 0.23-2.29 mg P gdw^{-1} and from 0.04-0.30 g m^{-2} respectively. Concentrations of melich P were significantly higher (in average about twice) in the 0-10 cm horizon while the opposite was true for concentration scaled to pool size (Tables 16, 18). Only in the 0-10 cm layer were P concentrations higher in the control than the burn-only (0.58 mg P gdw^{-1} lower), herbicide (0.58 mg P gdw^{-1} lower) and mechanical (0.53 mg P gdw^{-1} lower) treatments (Tables 16, 18).

Longleaf pine foliar C (%) ranged from 49.7% to 51.7% and there was no difference (P = 0.4688) among treatments. Similarly, total N (%) did not differ between treatments (P= 0.5192) and ranged from 0.8% to 1.1%. Harwood removal or prescribed burning did not affect either foliar ^{13}C (P = 0.4573) or ^{15}N (P= 0.2945). At last, foliar ^{13}C and ^{15}N expressed very little variability as they ranged from -28.5 to -27.4 (‰) and from -5.1 to -3.5 (‰) respectively.

Soil spatial heterogeneity

Spatial patterning was most pronounced for soil bulk density, bulk soil C and N concentrations and pools, and C:N ratios as indicated by significant distance effects (Table 19; Figure 41). Bulk soil characteristics did not exhibit any treatment by distance interactions. Soil bulk density was, on average, 7% lower at 1 m from the trunk than at 2 or 3 m, while bulk soil C and N concentration and pools were highest nearest the trunk (Figure 41). Treatment (restoration or reference) effects were only evident for total C and N concentrations and pools (Table 19; Figure 41). Carbon concentration was ~30% higher in the burn than the reference treatment, while C pools measured in the reference tended to be lower than the herbicide. Concentrations and pools of N were consistently lowest in the reference treatment (Figure 41).

Table 19. Results of a two-way ANOVA with repeated measurements on the effect of hardwood removal treatments and distance from the trunk on soil characteristics for 36 longleaf pine trees at Eglin AFB.

	Distance		Treatment		D x T	
Soil characteristics	**F value**	**P value**	**F value**	**P value**	**F value**	**P value**
Bulk Density (g cm^{-3})	10.10	0.0007	2.24	0.1382	1.88	0.0594
Moisture Content (%)	0.44	0.7313	1.19	0.3979	0.42	0.8728
C (%)	22.02	< 0.0001	3.44	0.0169	1.55	0.1655
N (%)	17.60	< 0.0001	6.40	0.0001	1.58	0.2716
C:N ratio	5.56	0.0147	1.65	0.1964	0.89	0.3952
C (g m^{-2})	13.97	0.0001	2.23	0.0883	1.12	0.2573
N (g m^{-2})	7.22	0.0055	3.68	0.0128	1.24	0.3679
NH_4 (g N gdw^{-1})	1.38	0.2621	1.15	0.3579	1.44	0.2041
NO_3 (g N gdw^{-1})	0.25	0.7777	3.42	0.0198	0.85	0.5669
NH_4 (g m^{-2})	0.85	0.4349	0.95	0.4512	1.60	0.1459
NO_3 (g m^{-2})	1.04	0.4563	2.28	0.0838	1.09	0.3871
Ammonification (g N $gdw^{-1}d^{-1}$)	0.17	0.8456	2.08	0.1091	1.13	0.3570
Nitrification (g N $gdw^{-1}d^{-1}$)	1.57	0.2186	2.74	0.0462	2.89	0.0099
Mineralization (g N $gdw^{-1}d^{-1}$)	0.28	0.7561	1.99	0.1203	1.40	0.2196
Ammonification (g N $m^{-2}d^{-1}$)	0.13	0.8749	1.75	0.1670	1.08	0.3889
Nitrification (g N $m^{-2}d^{-1}$)	1.57	0.2192	1.57	0.0428	2.74	0.0134
Mineralization (g N $m^{-2}d^{-1}$)	0.15	0.8626	1.90	0.1366	1.36	0.2355
Initial C flux rate (µg C gdw^{-1} h^{-1})	2.02	0.1325	0.70	0.6336	0.54	0.8020
6-week C flux rate (µg C gdw^{-1} h^{-1})	2.89	0.0386	1.01	0.6523	1.31	0.1730

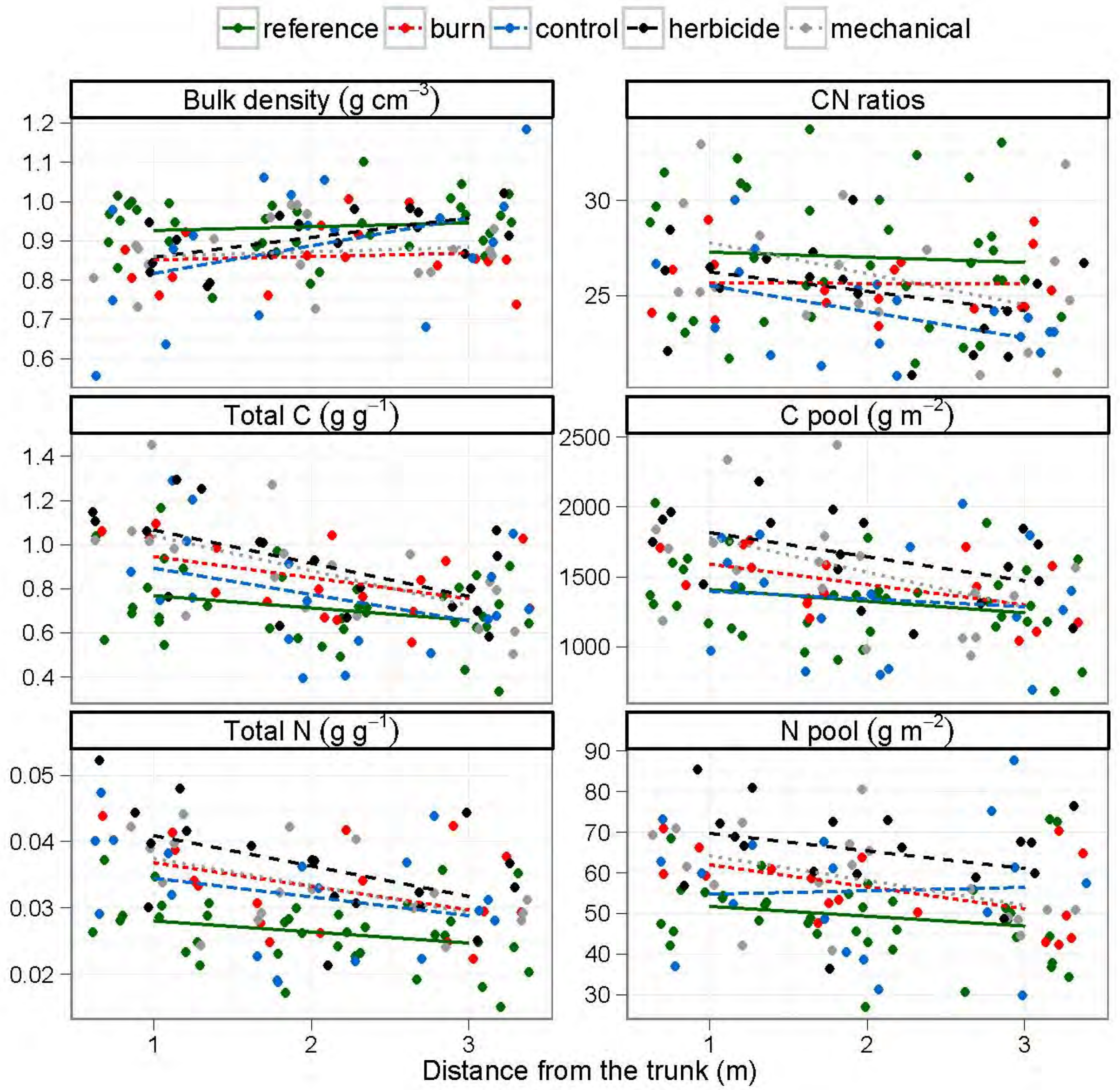


Figure 41. Results of a mixed linear model with repeated measurements on the effect of hardwood removal treatments and distance from the trunk on soil bulk density, moisture content, carbon, and nitrogen for 36 longleaf pine trees at Eglin AFB.

The interaction between distance and treatment was significant only for net nitrification rates (mass and volume basis) (Table 20; Figure 42). The control treatment exhibited distinctively higher net nitrification rates at 3m than 1m (Figure 42). We did not detect an effect of distance on N mineralization rates, but hardwood removal reduced extractable NO_3^- and NH_4^+ and net nitrification rates (mass and volume basis) (Table 20; Figure 42). We also observed a significant effect of distance on C flux rates (after a 6-week incubation) with microbial respiration rates 1.4 times higher near the trunk than outside the tree crown. The reference treatment showed lower (45-75%) inorganic N values than the control, and the difference between these two treatments was also substantial for nitrification rates.

Table 20. Results of a two-way ANOVA with repeated measurements on the effect of hardwood removal treatments and distance from trunk on vegetation abundances for 36 longleaf pine trees in longleaf pine forests at Eglin AFB.

	Distance		Treatment		D x T	
Plant functional group	**F value**	**P value**	**F value**	**P value**	**F value**	**P value**
Grasses	4.34	0.0075	0.67	0.8209	0.85	0.5966
Forbs	3.91	0.0125	2.33	0.0779	0.31	0.9857
Woody	0.42	0.7400	10.47	< 0.0001	1.94	0.0387
Saw palmetto	1.28	0.2857	4.53	0.0049	0.73	0.7185
Total	2.08	0.1080	0.48	0.7533	0.94	0.5153

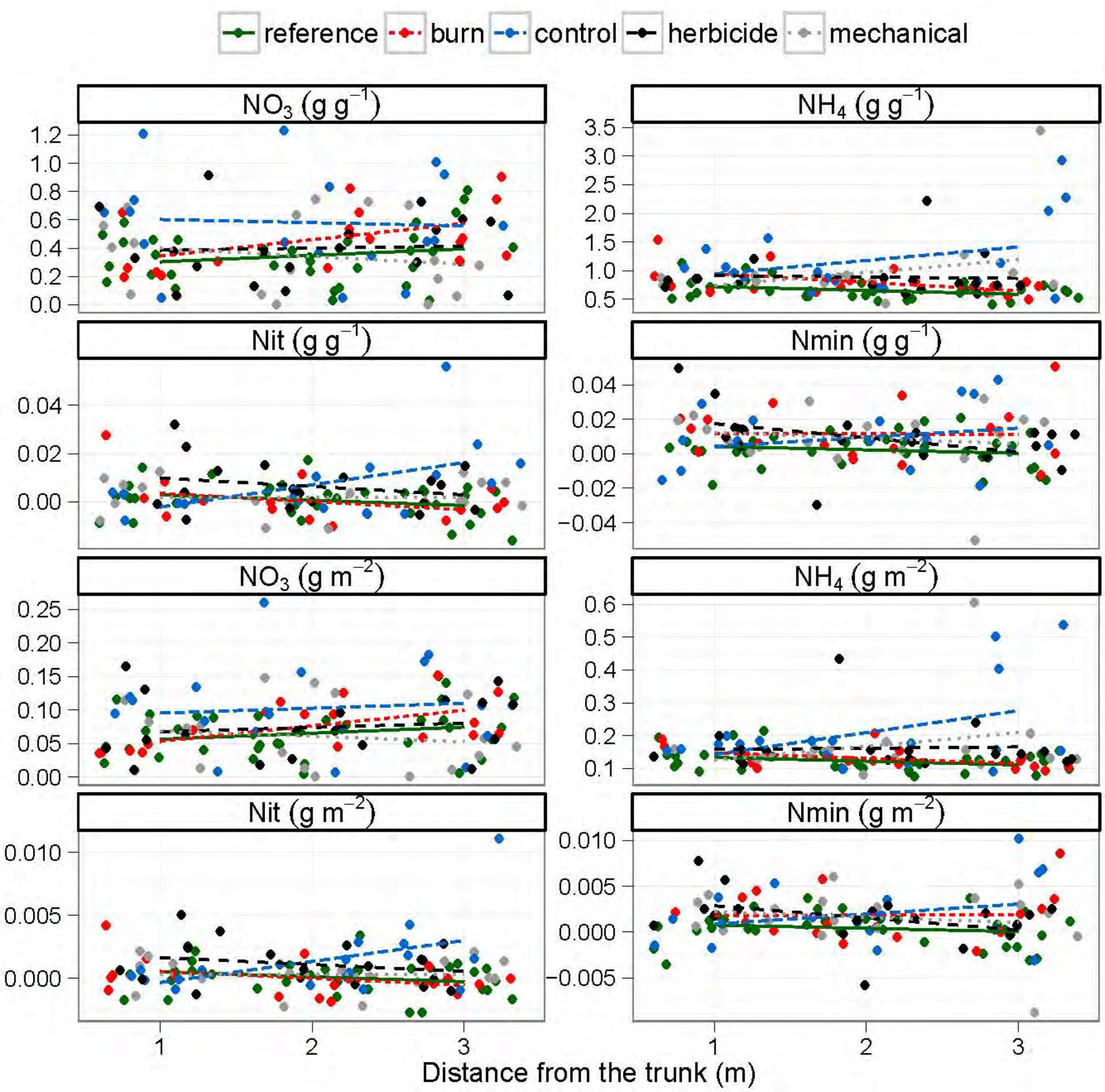


Figure 42. Results of a mixed linear model with repeated measurements on the effect of hardwood removal treatments and distance from the trunk on inorganic nitrogen for 36 longleaf pine trees forests at Eglin AFB.

We detected an interaction between treatment and distance for woody vegetation only (Table 20; Figure 43). The spatial pattern of woody vegetation in the herbicide treatment differed from the reference and mechanical treatments (Figure 43), which, respectively, showed decreasing and increasing gradients of woody vegetation as distance from the tree increased. In addition, grasses and forbs were respectively 24% and 34% lower 1 m from the trunk than 2 or 3 m away (Table 20; Figure 43). Finally, saw palmetto was significantly higher in the herbicide than any other treatments, while woody vegetation was at least 50% lower in the herbicide and burn treatments.

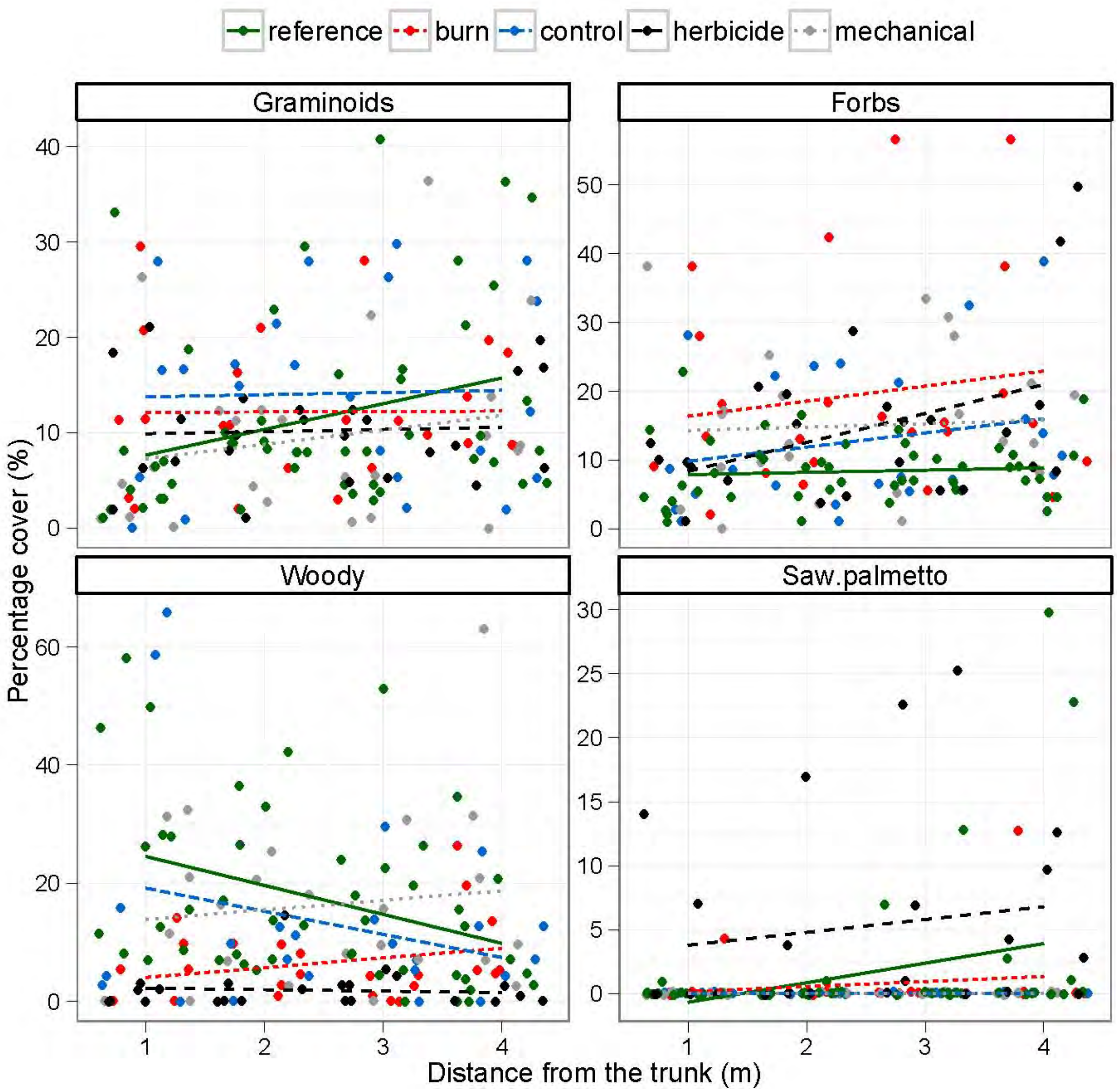


Figure 43. Results of a mixed linear model with repeated measurements on the effect of hardwood removal treatments and distance from the trunk on the understory vegetation abundances (%) for 36 longleaf pine trees forests at Eglin AFB.

4.2 RCW model validation results

After modifying how females move within the RCW population model, we found that the model's predictions generally were not significantly different from the actual population dynamics observed for the RCW populations in the Sandhills, MCBCL or Eglin AFB, with some exceptions (Table 21). For the Sandhills population, the means of the standard deviates for population size and the number of occupied territories, breeding females, and breeding males were not significantly different from zero, indicating that the predicted values for these parameters were not different from the values for the actual population. Similarly, the variances in standard deviates for population size and in the number of occupied territories and breeding females were not significantly different from one, indicating that the variation in these parameters was not different from the variation in these values among years in the actual population. However, the population model significantly over-predicted the number of solitary males, under-predicted the level of variation in the number of solitary males, and over-predicted the level of variation in the number of breeding males in the population compared to the actual population (Table 21; Figure 44).

Table 21. Results of model validation for the RCW population model version 2.0 using three populations of RCWs in the Sandhills of North Carolina, MCBCL, and Eglin AFB. The mean and variance of the standard deviates are given (methodology according to McCarthy and Broome 2000).

	Sandhills Population		***MCBCL Population***		***Eglin AFB Population***	
	Mean[1]	**Variance[1]**	**Mean[1]**	**Variance[1]**	**Mean[1]**	**Variance[1]**
Population Size	-0.10	0.30	-0.26	1.29	--------	--------
Number of Occupied Territories	0.27	0.40	-1.39*	0.59	1.00	1.81
Number of Breeding Females	0.05	0.26	-1.09*	0.41	--------	--------
Number of Breeding Males	-0.13	0.17*	-1.18	0.40*	--------	--------
Number of Solitary Males	0.75*	0.06*	0.02	0.21	--------	--------

[1] Model predictions are significantly different from actual population observations if the mean of the standard deviates is significantly different from zero or if the variance of the standard deviates is significantly different from one. Significant differences are indicated by an asterisk (*) at a significance of p <0.01.

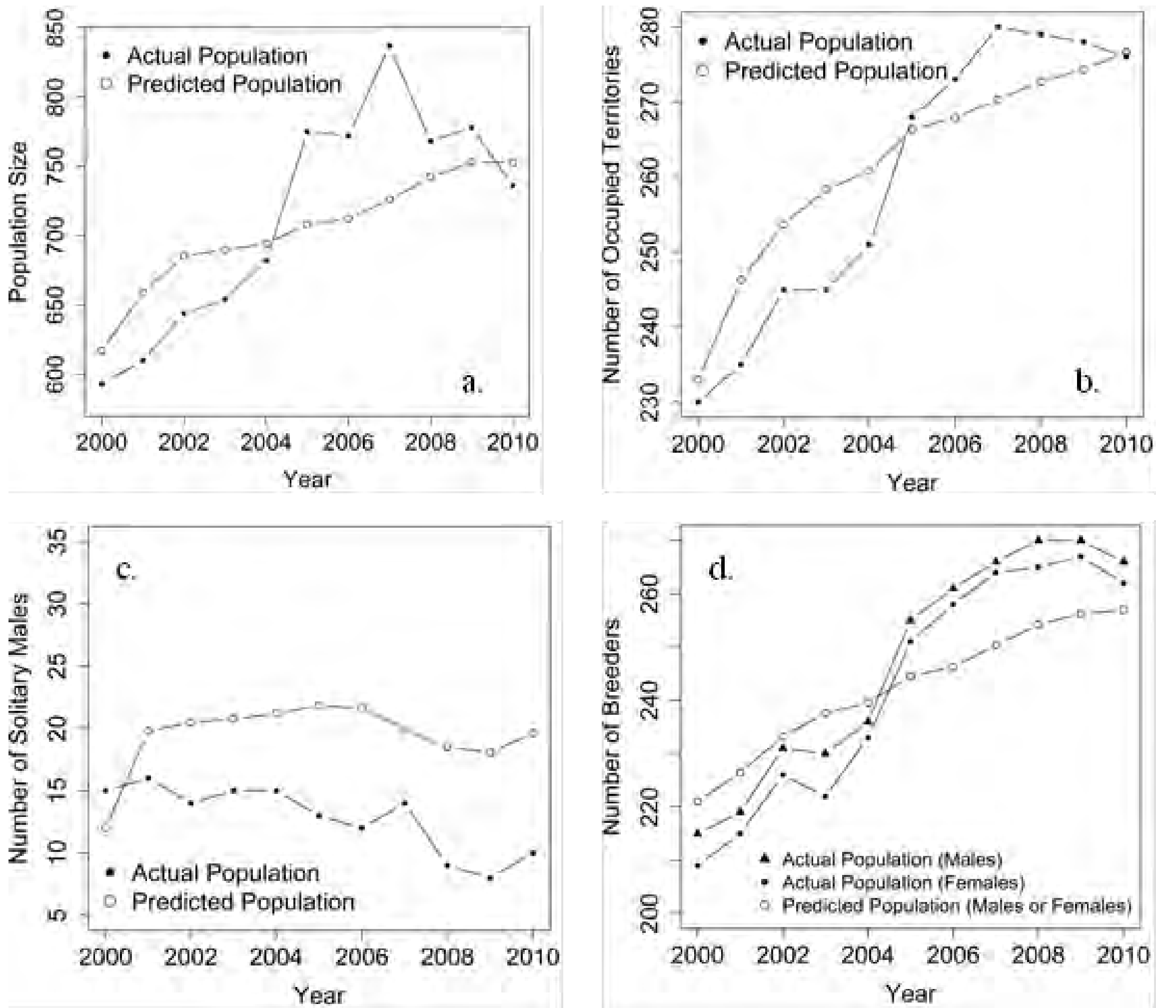


Figure 44. Trends in (a) population size, (b) the number of occupied territories, (c) the number of solitary males, and (d) the number of male and female breeders as predicted by the RCW population model (open circles) compared to those observed in the RCW population in the Sandhills region of North Carolina (closed symbols) from 2000-2010.

For the RCW population on MCBCL, the means of the standard deviates for population size and for the number of breeding and solitary males were not significantly different from zero, indicating that the predicted values for these parameters were not different from the actual ones observed in the population. In addition, the variances in the standard deviates for population size and for the number of occupied territories, breeding females, and solitary males were not significantly different from one, indicating that the predicted variances for these population components were not different from the variance among years actually observed. However, the population model significantly under-predicted the number of occupied territories, the number of breeding females, and the variance in the number of breeding males (Table 20; Figure 45).

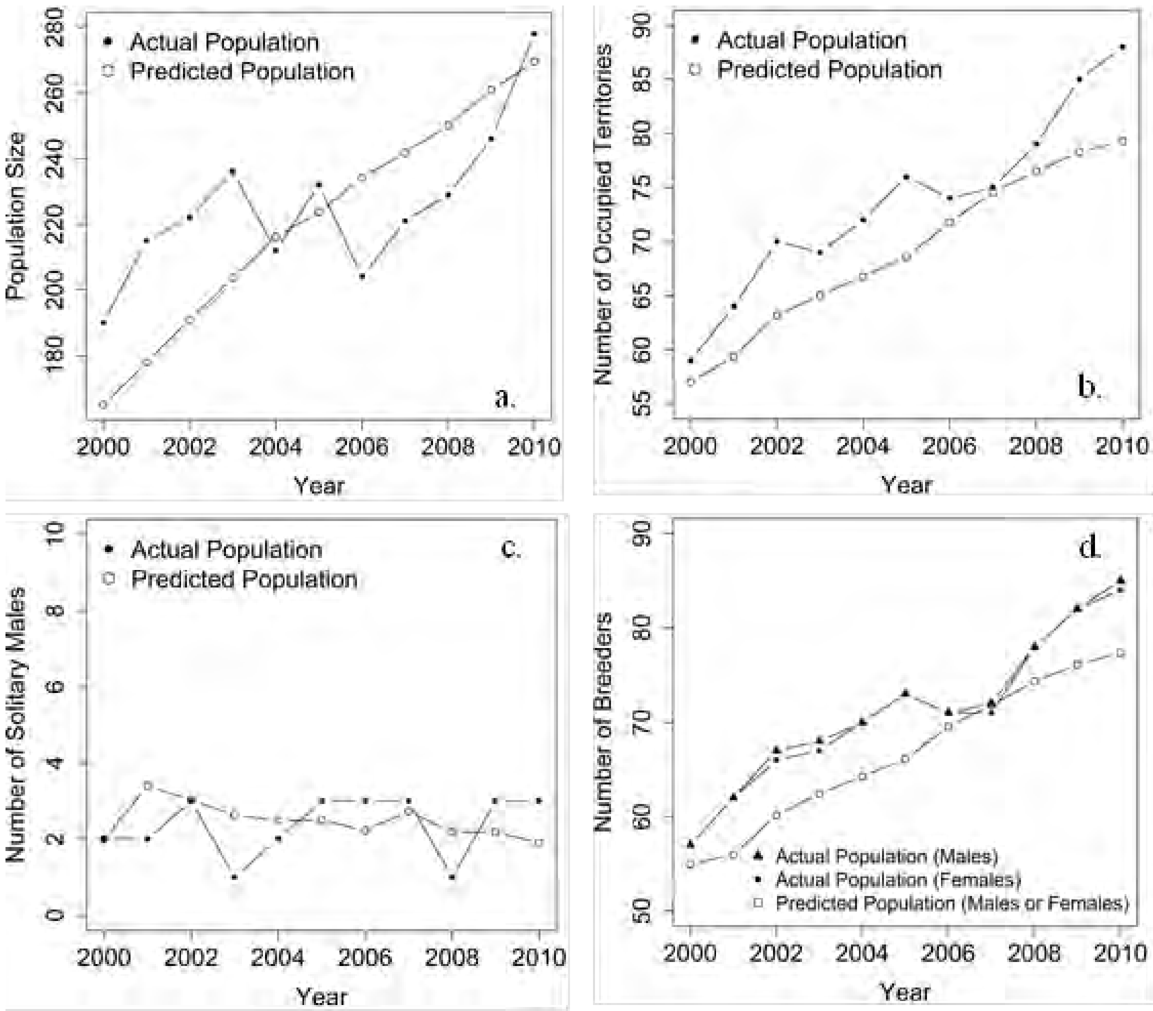


Figure 45. Trends in (a) population size, (b) the number of occupied territories, (c) the number of solitary males, and (d) the number of male and female breeders as predicted by the RCW population model (open circles) compared to those observed in the RCW population on MCBCL (closed symbols) from 2000-2010.

Finally, the model accurately predicted the number and variance of occupied territories at Eglin AFB (Table 21; Figure 46).

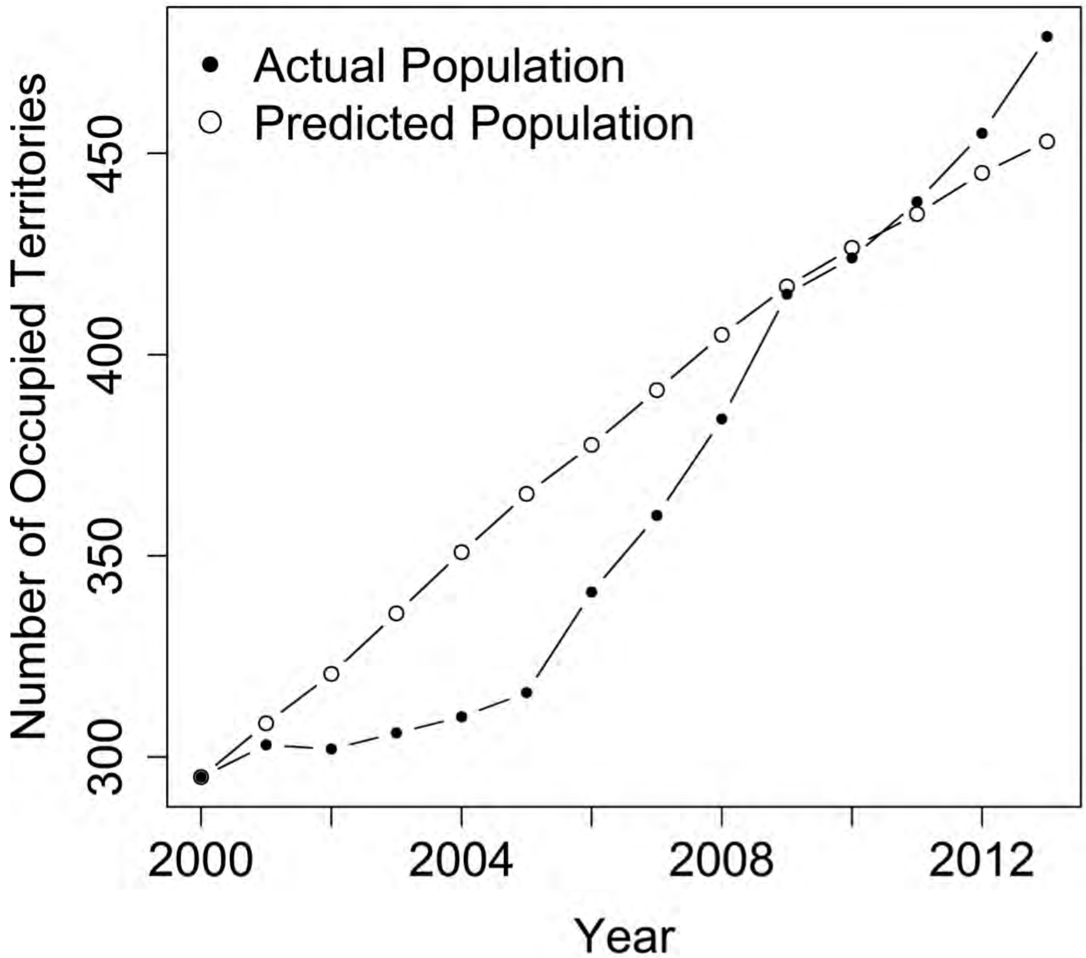


Figure 46. Trends in the number of occupied territories as predicted by RCW population model (open circles) compared to those observed in the RCW population on Eglin AFB (closed symbols) from 2000-2013.

4.3 ST SIM model validation results
4.3.1 Non-spatially explicit validation

The comparison between the distribution of the landcover state areas (Table 4; Figure 12) revealed that the reference and predicted distributions were significantly different for the years 2003, 2007, and 2010 ($p < 0.01$; results not shown). Therefore, the ST-SIM baseline model did not accurately predict the distribution of landcover states. However, it is unclear whether this result is due to the model's incorrect representation of ecosystem dynamics on Eglin AFB or, alternatively, to unavoidable errors in the reference landcover classifications.

As discussed previously, errors in a landcover state map used to initialize the ST-SIM model were propagated throughout the simulation. In this study, the 2001 reference map, created through the supervised classification of satellite imagery by staff at Eglin AFB, was found to have an accuracy level of 81% (kappa coefficient: 0.77). The most common errors in this dataset included the misidentification of Developed areas as Bare Land (17% of sampling points), Longleaf Pine as Mixed forest (18% of points), and Mixed forest as Hardwood forest (13%; Laine unpublished data). Similarly, we observed high levels of error between reference (based on the GIS maps) and predicted (based on the ST-SIM simulation) areas for the Developed (16.56 to

29.80%), Bare Land (-9.44 to -26.16%), Mixed (1.40 to -4.15%), Young Pine (-8.92 to -22.50%), and Longleaf Pine > 15 years (9.34 to 52.25%) landcover states.

Therefore, we hypothesize that significant differences between reference and predicted landcover state distributions were at least in part due to misclassifications in these state classes in the reference GIS maps used for validation and model initialization. In the model, a landscape cell misidentified in the 2001 landcover state map (used to initialize the model) would remain in that state for the duration of the simulation (with the exception of landcover states connected through succession, fire, or management). If that landscape cell was then correctly identified in a later reference landcover state map used for validation, the model would be unable to account for this change in state class, and the model prediction for that landscape cell would appear to be inaccurate.

Furthermore, assuming that similar classification errors are likely also present in the later reference maps, landscape cells correctly identified in the 2001 reference map could have been misidentified in the later reference maps used for validation, and this change in landcover state type would appear as an inaccurate prediction by the ST-SIM model. Generally, errors in the reference data used for validation purposes can make up a large proportion of the difference between predicted/classified landcover maps and the reference data (reviewed in Foody 2002).

The existence of errors of this nature is further supported by the unlikely temporal changes in certain landcover classes in the reference datasets shown in Figure 12 and Table 4. For example, between 2001 and 2010, the reference data show that Developed areas at Eglin AFB decreased, which is particularly unlikely given the pressure for existing military installations to house additional troops under the Base Realignment and Closure program. Similarly, given how long it would take for longleaf pine stands to succeed to mixed pine/hardwood stands, we hypothesize that the increase in Mixed forest from 116,666 acres to 123,348 acres in just four years has more to do with landcover classification errors than actual ecosystem dynamics.

Finally, we determined that the 2010 predicted landcover distributions for stochastic iterations 2 through 10 were not significantly different from that of iteration 1, illustrating that the model, despite being stochastic, produces statistically identical results in each iteration. Therefore, we recommend that, to save processing time, it may only be necessary to simulate 1 iteration of an ST-SIM model. In addition, the results of that 1 iteration can be used within the RCW DSS without requiring that landscape model predictions for several iterations be averaged together.

4.3.2 Spatially explicit validation

According to the spatially explicit validation of the landcover state maps as predicted by the ST-SIM model, we found that predictive maps had overall accuracy levels of 83.6-84.1% (depending on the iteration results used; kappa coefficient = 0.80 or 0.81 for all iterations; Table 22). Therefore, the ST-SIM model predictions met the minimum accuracy thresholds of 80% and 0.75 for overall accuracy and kappa coefficient, respectively, widely used in other studies (Fleiss 1981, Foody 2002).

Table 22. Accuracy assessment for predictive state class maps produced by the ST-SIM baseline simulation relative to the 2010 reference landcover map of Eglin AFB (model initialization year = 2001).

Model Iteration	Overall Accuracy (Observed Agreement)	Chance Agreement	Kappa Coefficient
1	83.8%	15.7%	0.81
2	83.8%	15.7%	0.81
3	83.9%	15.8%	0.81
4	84.1%	15.7%	0.81
5	83.8%	15.7%	0.81
6	83.6%	15.7%	0.80
7	84.0%	15.7%	0.81
8	84.1%	15.7%	0.81
9	84.1%	15.7%	0.81
10	84.0%	15.8%	0.81
2001 landcover map[1]	81%	18%	0.77

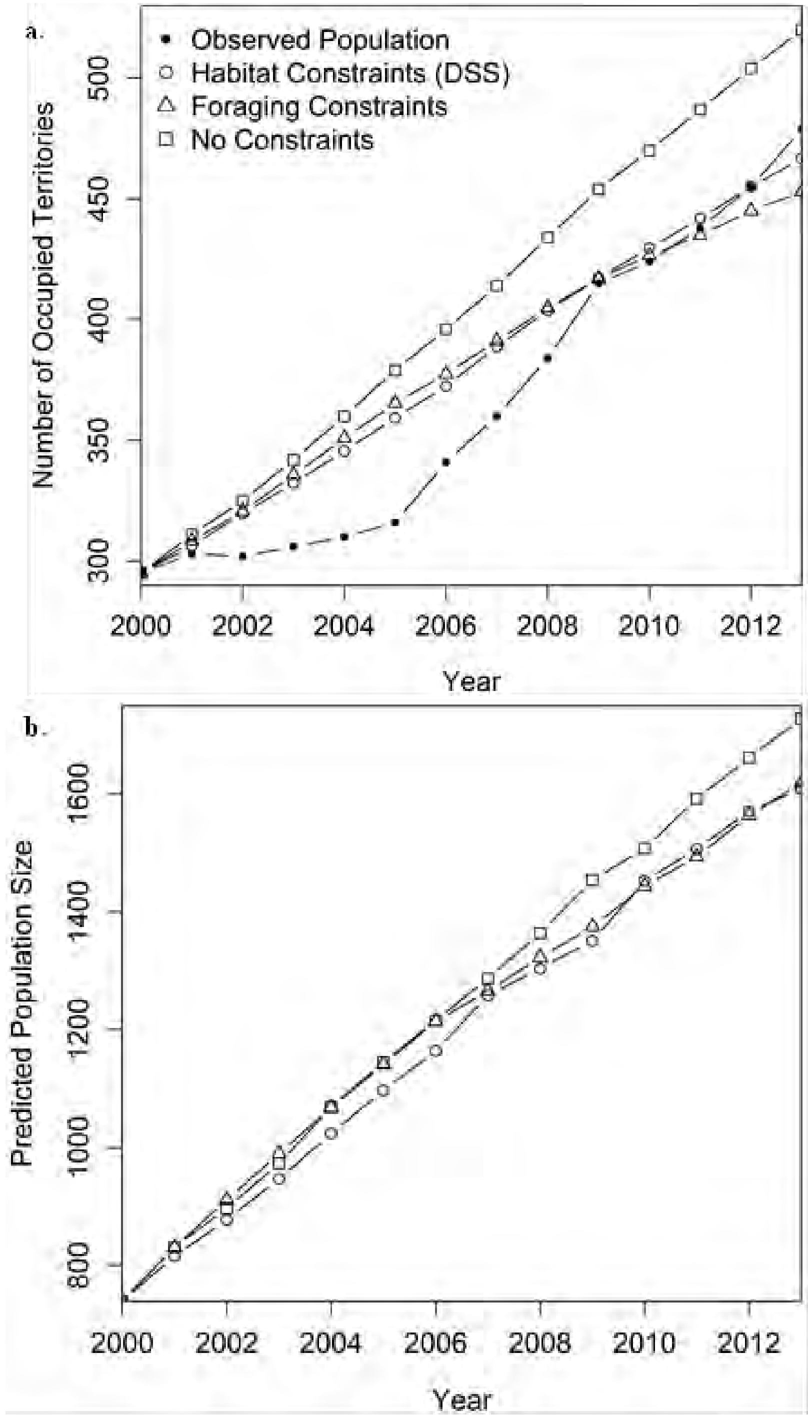
[1]This map indicated the total area and distribution of each state class at the start of the **ST-SIM** model used for validation. Accuracy in this classified map was previously assessed by staff at Eglin AFB Base. Any errors in this landcover map would be propagated through the simulation and could ultimately influence accuracy assessment results.

In summary, we maintain that the ST-SIM model that we developed to represent the current landscape states, natural transitions, and management regimes is an accurate representation of the longleaf pine ecosystem at Eglin AFB. Although we found a significant difference between the landcover state area distributions in the reference and predicted landcover maps, we assert that the inaccuracies were largely the result of misclassified landcover types in the reference datasets. In addition, the ST-SIM model was still able to capture approximate trends in landcover dynamics and had a relatively high accuracy level according to the spatially explicit analysis. Furthermore, even if the model did not make accurate quantitative predictions of landcover distribution, models like the ST-SIM landscape model for Eglin AFB can still act as important tools for evaluating the relative impacts of development projects, ecosystem management activities, and other forms of landcover change through time (Beissinger and Westphal 1998, Crone et al. 2011). Such applications are described in Section 3.5.

4.4 RCW DSS validation and simulation results

We found that the predictions of the RCW DSS version 3.0 (Habitat Constraints scenario) were significantly different from the actual population dynamics observed at Eglin AFB (Table 5; Figure 47). The mean of the standard deviates for the number of occupied territories (0.95) was significantly different from zero (*p*-value = 0.003), indicating that the predicted values for this parameter differed from those actually observed. However, the model accurately predicted territory occupancy in the final years of the simulation; significant differences between the observed and predicted number of occupied territories arose because territory occupancy stabilized for 5 years before increasing relatively sharply for the remainder of the study period in the actual population. The RCW population model did not account for these changing rates of territory occupancy through time, instead predicting a steady increase in territory occupancy (Figure 47). In contrast, the variance in the standard deviates (0.86) was not significantly

different from 1, indicating that the predicted variance in the number of occupied territories did not differ from that actually observed.



[1]In the "Habitat Constraints Scenario", we predicted territory occupancy with the RCW DSS, incorporating changes in landscape suitability on RCW population dynamics at time steps 5 (2005) and 10 (2010).
[2]For the "Foraging Constraints Scenario", we selected "Constrain using nesting and foraging habitat" as the landscape option with a minimum acreage of 150, ultimately operating the RCW population model according to version 2.0 program routines. Simulation originally described in Section 3.2.

[3]In the “No Constraints Scenario”, we selected the “No constraints” landscape option and did not consider any area or suitability constraints on the availability or placement of new RCW territories through time.
[4]We did not use or report the observed population size for Eglin AFB, because only a subset of the population is monitored and the full population size is unknown.

Figure 47. Number of occupied territories and population size as predicted by the Habitat Constraints[1] (open circle), Foraging Constraints[2] (triangle), and No Constraints[3] (square) scenarios. We validated the RCW DSS by comparing number of occupied territories predicted by the Habitat Constraints scenario with the number of territories observed in the actual RCW population at Eglin AFB[4].

We also found that the manner in which the landscape and landscape change are considered had a substantial impact on model predictions (Figure 47). The Habitat Constraints scenario (which used habitat suitability-based rules for the addition of recruitment clusters, budding, and initial cluster abandonment) predicted territory occupancy levels that more closely mirrored observed territory occupancy at Eglin AFB compared to the Foraging Constraints scenario (which only considered territory area; Figure 47a). However, the predictions of these scenarios did not differ significantly from the observed population or from each other. Furthermore, the No Constraints scenario (which used neither habitat suitability- or area-based rules for recruitment clusters, buds, or territory abandonment) substantially overestimated the number of occupied territories on the landscape (Figure 47a). This translated to a much larger predicted population size for the No Constraints scenario (1,728 RCWs by year 2013) compared to the Habitat (1,609 RCWs) and Foraging (1,619 RCWs) constraints scenarios (Figure 47b).

4.5 DSS management scenarios

According to the non-spatially explicit results of the ST-SIM landscape model alone, the proportion of the landscape in each habitat suitability class varied significantly from that of the Status Quo scenario for every alternative management scenario (Table 23; Figure 19). Of particular note, the Non-Longleaf Management scenario, in which we examined the impacts of more aggressively restoring hardwood, mixed, and sand pine forest types at the expense of maintaining a wider area of Eglin AFB, resulted in the greatest increase in the area of the landscape representing average, good, and excellent habitat quality (suitability = 3, 4, and 5) over the Status Quo scenario (Table 23; Figure 48). The Fire 200K scenario, in which we increased the area burned by prescribed fires each year from 104,000 to 200,000 acres, and the Fire Restoration scenario, in which we assumed that less suitable longleaf pine states would be preferentially burned, were the only other scenarios that resulted in an increase in the amount of average, good, and excellent suitability habitat throughout Eglin AFB compared to the current management regime (Table 23; Figure 48). A discontinuation of all landscape management efforts in the No Management scenario resulted in the most substantial decline in the amount of average, good, and excellent suitability habitat compared the Status Quo scenario (Table 23; Figure 48). In addition, restricting all landscape management efforts to the LCCA scenario and reducing the amount of the landscape burned through prescribed fires to 50,000 acres per year (Fire 50K scenario) also resulted in a decline in the amount of average, good, and excellent suitability habitat versus the Status Quo scenario (Table 23; Figure 48).

Table 23. ST-SIM landscape model predictions for the area (acres) of landcover states at Eglin AFB after 30 years under several management scenarios[1]. The landscape model was initialized under the same starting conditions (the "initial" column) for all scenarios.

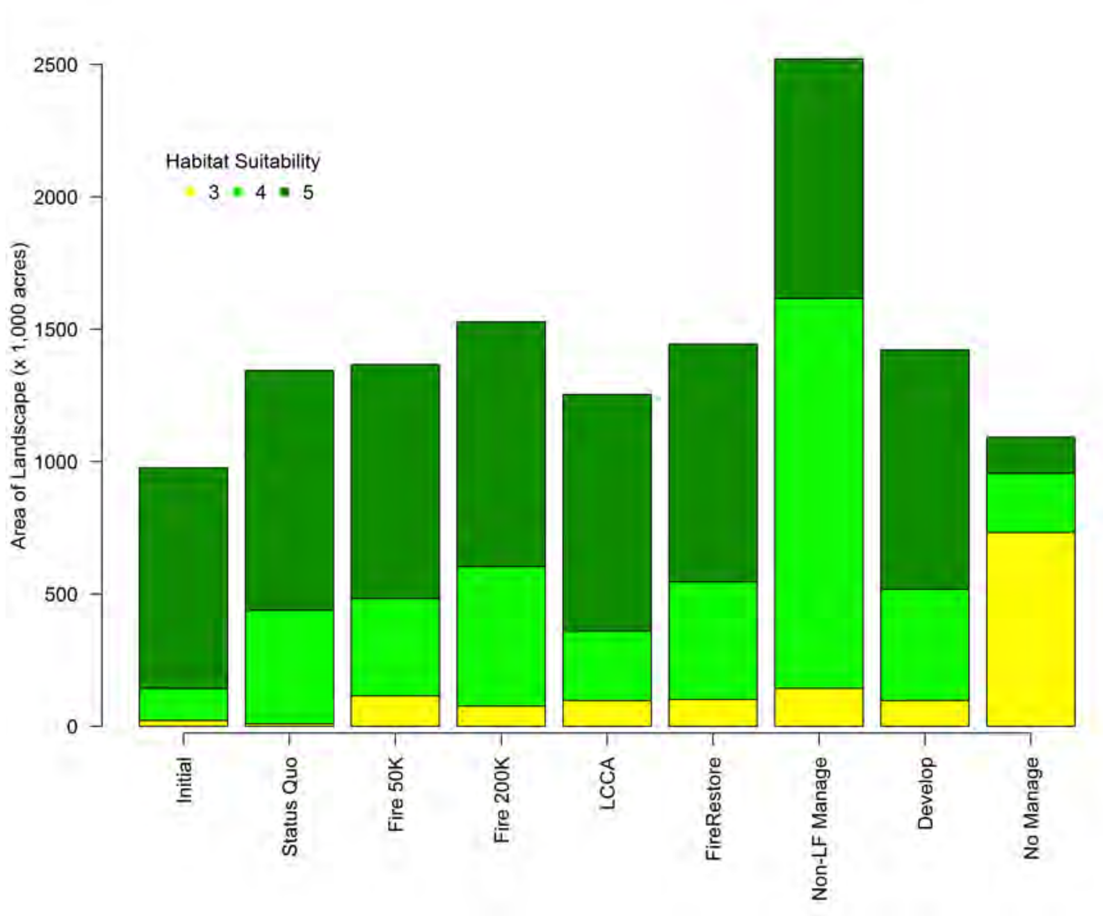
		Area (acres)								
State	**Suitability**	*Initial*	*Status Quo*	*Fire 50K*	*Fire 200K*	*LCCA*	*Fire Restore*	*Non-LF Manage*	*Develop*	*No Manage*
Developed	1	5632	5632	5632	5632	5632	5632	5632	9289	5632
Bare Land	1	66701	66701	66701	66701	66701	66701	66701	65755	66701
Sand Pine	1	73759	49067	49084	49149	60990	24187	31345	48795	49082
Mixed	1	122653	122219	122206	122232	122390	46751	48676	121141	122211
Hardwood	1	51602	51249	51243	51221	51312	39743	39895	51254	51248
Young Pine	1	12540	193	220	136	145	115	80	170	83
LLP15-LowCanBA:High-High	3	12289	4965	4639	5806	4341	4942	5432	5136	647
LLP15-LowCanBA:High-Low	1	0	136	197	1	31	88	108	107	930
LLP15-LowCanBA:Mod-High	2	148	194	290	0	328	335	371	110	673
LLP15-LowCanBA:Mod-Low	1	696	316	400	0	962	266	337	251	2750
LLP15-LowCanBA:Low-Low	1	3345	192	212	157	506	171	236	158	271
LLP15-SuitCanBA:High-High	3	9337	1688	1653	1793	1670	1675	1667	1704	133
LLP15-SuitCanBA:High-Low	2	0	0	0	0	0	0	0	0	0
LLP15-SuitCanBA:Mod-High	2	28	40	49	0	52	51	78	21	295
LLP15-SuitCanBA:Mod-Low	2	180	53	69	0	69	53	44	51	920
LLP15-SuitCanBA:Low-Low	1	641	5	11	12	13	10	6	13	18
LLP15-HighCanBA:High-High	2	201	8798	7361	12708	6063	7415	7957	8709	1702
LLP15-HighCanBA:High-Low	1	0	1464	2073	3	325	1861	2490	1513	5382
LLP15-HighCanBA:Mod-High	2	0	471	664	33	520	986	661	509	766
LLP15-HighCanBA:Mod-Low	1	1	1062	1539	1	1969	1571	1447	1048	3031
LLP15-HighCanBA:Low-Low	1	26	1037	1177	0	3655	1063	1140	909	2893
LLP60-LowCanBA:High-High	4	11558	41454	34894	51550	25115	145263	134889	40714	12121
LLP60-LowCanBA:High-Low	2	0	7215	11731	779	2377	9325	12571	7511	24758
LLP60-LowCanBA:Mod-High	3	262	1191	2176	0	1778	6694	3866	1219	3851
LLP60-LowCanBA:Mod-Low	2	890	2240	3551	0	7244	2839	2815	1914	11636
LLP60-LowCanBA:Low-Low	1	4164	372	413	330	4641	282	346	297	446
LLP60-SuitCanBA:High-High	5	83383	90604	88499	92522	89439	90546	89423	90357	13715
LLP60-SuitCanBA:High-Low	3	0	921	1649	11	355	445	541	922	40826
LLP60-SuitCanBA:Mod-High	4	109	516	1001	0	718	1087	2000	547	9914
LLP60-SuitCanBA:Mod-Low	3	127	651	1282	0	1562	508	590	669	27688
LLP60-SuitCanBA:Low-Low	2	1312	88	71	53	462	71	80	63	104
LLP60-HighCanBA:High-High	4	315	951	836	1108	487	1049	477	868	296
LLP60-HighCanBA:High-Low	2	0	188	286	0	22	130	4	133	903

LLP60-HighCanBA:Mod-High	3	0	29	57	0	15	37	28	35	100
LLP60-HighCanBA:Mod-Low	2	1	36	75	0	51	47	5	46	214
LLP60-HighCanBA:Low-Low	1	37	0	0	0	2	0	0	0	0
Water	1	1845	1845	1845	1845	1845	1845	1845	1845	1845
Suitability Score 1	1	343643	301490	312523	302545	304311	302952	297455	297420	300604
Suitability Score 2	2	2760	19323	41970	19067	26738	24147	14084	13574	18805
Suitability Score 3	3	22015	9445	73245	9685	13839	11455	7717	7609	10066
Suitability Score 4	4	11982	42922	22331	42129	34379	36731	51978	52659	44360
Suitability Score 5	5	83383	90604	13715	90357	84517	88499	92550	92522	89949

[1]Management scenarios included:

- Status Quo (Status Quo scenario): no changes to the current landscape management regime (i.e., the baseline ST-SIM model);
- Fire50K (Fire 50K scenario): annual target of 50,000 acres for prescribed burning (50% of Status Quo target);
- Fire200K (Fire 50K scenario): annual target of 200,000 acres for prescribed burning (twice the Status Quo target);
- LCCA scenario: all prescribed burning confined to the area of the LCCA (Figure 18);
- Fire Restore (Fire Restoration scenario): areas of lower suitability are preferentially managed at the expense of maintaining areas of higher suitability;
- Non-LF Manage (Non-longleaf Management scenario): a higher area of hardwood and mixed forest stands are treated with herbicide and mechanical midstory removal at the expense of managing longleaf pine stands;
- Develop (Development scenario): all habitat within a specific 3,676 acre plot is lost to development (Figure 18);
- No Management (No Management scenario): the landscape is not managed in any way (no prescribed burning, herbicide, or mechanical midstory removal).

The alternative management regimes had smaller impacts on the amount of excellent quality (suitability = 5) habitat compared to the Status Quo scenario (Table 23; Figure 48). Only a doubling of prescribed burning efforts (Fire 200K scenario) resulted in an increase in excellent quality RCW habitat (Table 23; Figure 48). All other management regimes led to a decrease in this habitat category, particularly the No Management scenario (Table 23; Figure 48). However, most of these alternative management regimes only resulted in minor decreases in excellent quality habitat: the Development, Fire Restoration, LCCA, and Non-Longleaf Management scenarios reduced excellent quality habitat by approximately 1,000 acres or less compared to the Status Quo scenario (Table 23; Figure 48).



[1]Management scenarios included:

- Status Quo: no changes to the current landscape management regime (i.e., the baseline ST-SIM model);
- Fire 50K: annual target of 50,000 acres for prescribed burning (50% of Status Quo target);
- Fire 200K: annual target of 200,000 acres for prescribed burning (twice the Status Quo target);
- LCCA: all prescribed burning confined to the area of the Core Conservation Area (Figure 18);
- FireRestore: areas of lower suitability are preferentially burned at the expense of maintaining areas of higher suitability;
- Non-LF Manage: a higher area of hardwood and mixed forest stands are treated with herbicide and mechanical midstory removal at the expense of managing longleaf pine stands;
- Develop: all habitat within a specific 3,676 acre plot is lost to development (Figure 18);
- No Manage: the landscape is not managed in any way (no prescribed burning, herbicide, or mechanical midstory removal).

Figure 48. ST-SIM landscape model predictions for the area of average (value = 3, yellow), good (value = 4, light green), and high (value = 5, dark green) suitability habitat for RCWs at Eglin AFB after 30 years under several management scenarios[1]. The landscape model was initialized under the same starting conditions (the "initial" bar on far left) for all scenarios.

These results are in keeping with general observations and field experiments that investigated the impacts of landcover management on habitat quality in longleaf pine ecosystems. Observations of several longleaf pine woodlands found that these ecosystems ultimately developed into forests of mixed pine and xeric/mesic hardwoods (Veno 1976, Myers 1985) that are unsuitable for RCWs (Hooper and Lennartz 1981, Repasky 1984, Porter and Labisky 1986, Bradshaw 1995, Hardesty et al. 1997) without fire and other habitat management efforts. Similarly, our modeling results indicate a relatively rapid loss of suitable RCW habitat without management intervention. In addition, increasing the landscape area burned each year had the largest positive impact on the highest quality RCW habitat in our management scenarios. This result is supported by several field experiments by Provencher et al. (2001a, 2001b, 2001c, 2002a, 2002b, 2002c), who showed that fire restored plant, arthropod, herpetofauna, and bird communities at Eglin AFB to reference conditions faster and more completely than other management techniques.

When we linked the ST-SIM landscape model results to the RCW population model as described in Section 3.4, we detected a bug in the RCW population model that allowed the model to add new RCW budded territories anywhere throughout the base (e.g., open areas). This caused a significant over-prediction in population size (results not shown). Therefore, we ran one additional simulation to demonstrate an alternative method for linking the two models that would allow for predictions of how landscape-level changes could impact the RCW population at Eglin AFB. In the RCW population model, we used nesting and foraging area constraints, as opposed to habitat suitability constraints, as the landscape option. In this simulation, new territories needed to meet only minimum size constraints (here, 120 ac), and the model operated under the RCW population model version 2.0 capabilities (see Section 3.2). Because this landscape option does not consider landscape changes through time, we converted the predictive 2040 landcover state map produced by the No Management scenario in the ST-SIM landscape model to a polygon layer with landcover types recognized by the RCW population model. This predictive map was then used as the initial landscape layer in the RCW population model. Thus, this simulation used a predictive landcover layer representing landscape conditions for 2040 and an initial RCW cluster layer for 2013 representing the locations of actual territories to date. We ran this additional simulation of the No Management scenario for 30 years.

The predictions of the simulation operating under nesting and foraging area constraints produced results more in keeping with our expectations. This model predicted that the population would produce only one new budded territory on average each year and that these new territories would only be constructed in forested areas (Figure 49). Under this parameterization, the model predicted a modest increase in population size for the first 10 years, after which the population stabilized and then began to decline (Figure 50). If landscape management efforts were to be discontinued on the base, we would expect population trends similar to those predicted by the static nesting and foraging area constraints scenario. We would predict that the population would increase slightly as RCWs moved into existing but empty areas of suitable habitat but that the population would then stabilize and finally decline as high quality habitat was not maintained.

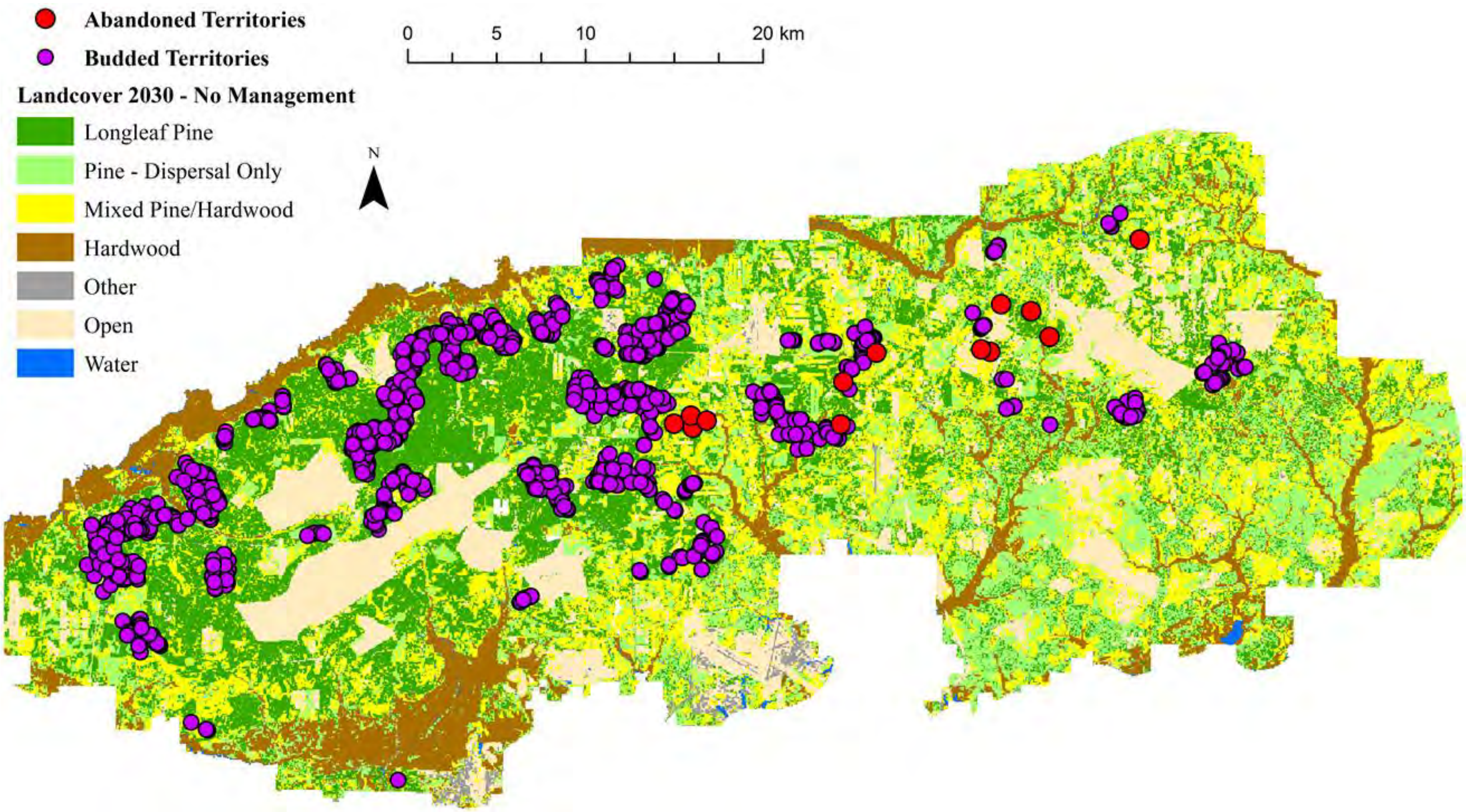


Figure 49. Predicted locations for new RCW territories on Eglin AFB (i.e., “budding locations”; purple circles) and for territories frequently abandoned (i.e., 5 or more times; red circles) over 70 iterations of a 30-year simulation of the RCW population model. The results shown here are from a scenario where we assumed that all landscape management efforts would be discontinued for those 30 years and that new territories would need to meet minimum size constraints.

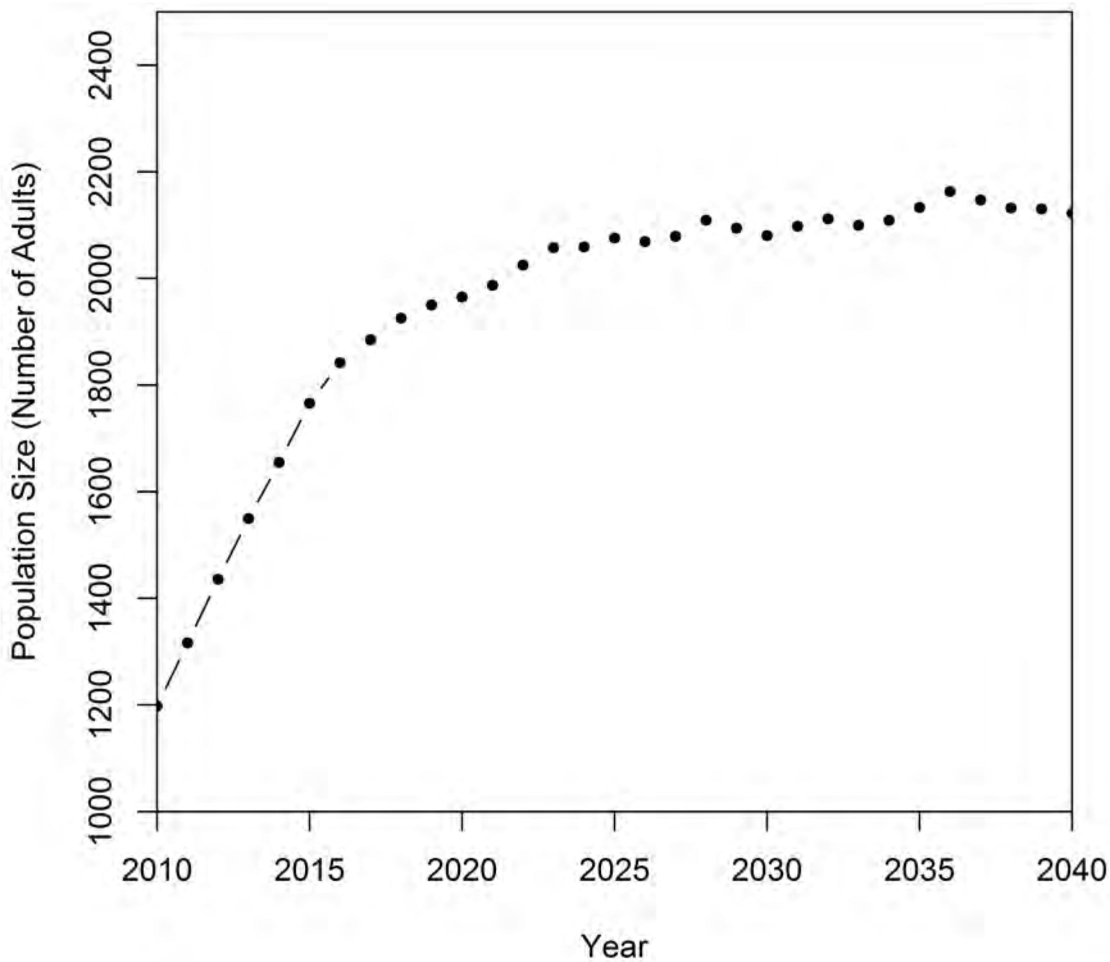


Figure 50. RCW population size predictions made by the RCW population model in which we assumed that (*i*) all landscape management efforts would be discontinued over a 30 year period and (*ii*) new territories could form as long as they met area requirements (all territories must be 120 ac or larger). This simulation was initialized with a landcover map representing predictive landcover conditions in the year 2040, and the model operated under version 2.0 capabilities.

In summary, the only successful RCW DSS simulation run to date employs the Nesting and Foraging Habitat Constraints option and considered only a landscape where management efforts have been discontinued for 30 years. Prior to publication, we plan to run simulations for all scenarios using habitat suitability constraints. Currently, a programming error is causing an over-prediction in the production rate and placement of new territory buds, ultimately resulting in an overestimation of RCW population size and territory occupancy, when the RCW population model is operated with habitat suitability constraints. We will rectify this problem and describe corrected results in future publications.

Despite lingering programming errors within the Habitat Suitability Constraints landscape option in the RCW population model, the ST-SIM landscape and the RCW population models, both alone and together in the RCW DSS, offer powerful tools for natural resource

managers. This section demonstrated how resource managers can make small changes to the baseline conditions of the ST-SIM landscape model to evaluate both landscape- and population-level responses to changes in current management regimes. Managers can modify the total area treated by specific management techniques (e.g., the Fire 50K and Fire 200K scenarios), the landcover types targeted for those management efforts (e.g., the Fire Restoration and the Non-Longleaf Management scenarios), or the location of targeted management efforts (e.g., the LCCA scenario). Managers can also explore the effects of discontinuing (e.g., the No Management scenario) or adding (e.g., the use of more aggressive management techniques for removing sand pine; example scenario not provided) management activities. By forcing the conversion of landcover types to developed or open areas, managers can also evaluate the relative impacts of building infrastructure or training facilities at specific locations on the base (e.g., the Development scenario). Finally, managers can explore the impacts of other landscape-mediated threats, such as hurricanes and the spread of invasive sand pine, on habitat availability by incorporating additional pathways in the ST-SIM landscape model.

Furthermore, in this report, we primarily discuss how the non-spatially explicit results of the ST-SIM landscape model can be used to evaluate associated changes in the amount of RCW habitat under alternative management regimes. In addition to this application, users could also use spatially explicit results of the ST-SIM landscape model (i.e., maps showing both the amount and specific configuration of habitat) in the RCW DSS to evaluate how certain alterations to the landscape, while affecting the same area, could have different impacts on the RCW population depending on the exact locations of those alterations. For example, natural resource managers could evaluate the impacts of a planned development project at multiple potential locations to determine which location posed the least threat to the RCW population. Although we did not show example applications of the spatially explicit ST-SIM landscape model results, these results can also provide powerful information for use by managers.

In addition, although the habitat suitability landscape option does not operate as intended at the moment, the RCW population and the ST-SIM landscape models can still be linked in the RCW DSS at this time. Users simply need to select the Nesting and Foraging Area Constraint option in the RCW population model and then use a predictive landcover map produced by the ST-SIM landscape model as the initial landscape layer. Although this parameterization does not allow dynamic changes to the landscape through time, it still allows a user to predict how the RCW population will ultimately respond to future modifications in habitat area and configuration – the primary intention of this research project.

5. Conclusions, Technology Transfer, and Implications for Future Research

5.1 Key Conclusions from Field studies

Fifteen years of vegetation data suggests a positive restoration trajectory of degraded longleaf pine sandhills regardless of initial restoration treatment, when fire is applied frequently following treatment. The underlying rationale that differences in vegetation trajectories might occur over time was that initial removal of midstory hardwood trees might affect the rate of ground cover response through reduced competition for light and increased fine fuel loading and continuity, resulting in less patchy fire that would control further woody stem recruitment and encourage herbaceous vegetation. Evidence from our study indicates that this projected outcome due to midstory removal did not materialize. Instead, the correlation of change in vegetation with fire frequency associated with all treatments, rather than limited to midstory removal treatments, supports prior findings of Hiers et al. (2007). In that study, the role of forest floor

litter and duff accumulation in fire-excluded sandhill sites was identified as a major cause of reduced vigor of ground cover as opposed to midstory oak BA or stem density. It is unclear if the initial reduction in species richness in herbicide plots was due to elimination of non-target species sensitive to hexazinone or to mortality of perennial species as a result of increased dead woody debris and long-duration smoldering in subsequent prescribed fires (Provencher et al. 2001a). The increased species richness at the smallest scale coupled with a greater abundance of ruderal species in herbicide versus other treatments by 2010 may reflect a recruitment response consistent with patches exposed to prolonged elevated temperatures and altered soil nutrient conditions (Creech et al. 2012). Increased ground cover stem density of *Quercus geminata* with midstory mechanical removal reveals a sprouting response that was not controlled by successive prescribed fires.

Over the long-term, application of herbicide followed by prescribed burning was the only method that restored bird assemblages to the reference condition, although species positively associated with longleaf pine in reference condition responded positively to all treatments. Occupancy probabilities for these species on all treatment sites were indistinguishable from those on reference sites by the conclusion of the study. Initially, reptile assemblages within treatment sites treated with prescribed burning alone were most similar to those of reference sites; fire surrogates did not immediately provide an observed benefit. At the conclusion of the study, reptile assemblages at all sites were indistinguishable from those on reference sites except for assemblages on sites treated with herbicide, suggesting herbicide application was relatively ineffective at restoring reptile assemblages. Overall, effective restoration of wildlife populations and assemblages in fire-suppressed longleaf pine sandhills was achieved and prescribed burning over approximately a decade was generally sufficient to achieve this result. In general, there was little observed benefit or need to employ fire surrogates prior to prescribed burning.

The lack of differences in soil C and N between the reference and the fire-suppressed plots prior to the treatments, despite the structural differences in communities, suggests that soil C and N are relatively stable regardless of fire history. This study also showed that the restoration treatments had a short term effect on reducing soil C (<3 years). The fact that the herbicide treatment was still different from the reference plots 15 years after the initial treatments, was perhaps attributable to the additional litter associated with herbicide treatment resulted in greater severity of fire and consumption of C. Thus, this study suggests that repeated fires (or lack of) or hardwood removal treatments have little detectable effect on soil nutrients in these nutrient-poor ecosystems.

We recommend that in fire-excluded longleaf pine sandhill sites, midstory hardwood reduction should be re-evaluated as a requisite restoration technique to advance or maintain diverse ground cover vegetation. These findings expand on growing evidence that a greater focus on reintroduction of frequent prescribed fire, rather than mechanical or chemical hardwood reduction, is warranted as the primary tool for restoration of fire-excluded sandhill sites.

5.2 Implications for Future Research

It is important to emphasize that these results are from xeric longleaf pine ecosystems, and consequently, the conclusions regarding treatment applications may not necessarily be appropriate for fire-excluded longleaf pine sites which occur in more mesic and productive conditions. Midstory encroachment on more mesic sites may include a different suite of midstory species (Brockway and Outcalt 2000, Kirkman et al. 2007, Freeman and Jose 2009, Outcalt and Brockway 2010). While longleaf pine ecosystems are often considered along a gradient of

edaphic conditions, xeric longleaf pine ecosystem response may represent a different mechanistic process rather than degree of gradation from more mesic longleaf pine ecosystems, thus, to further the applicability of these findings to a wider range of conditions will require further research.

This study also does not address the possibility of a threshold density of hardwoods or guild of midstory encroachment in which herbicide may provide an optimal outcome. Guilds, such as evergreen or semi-deciduous oaks, once established, have been suggested to limit restoration progress on similar sites (Hiers et al. 2007, Veldman et al. 2013) or even other ecosystems (Brudvig and Asbjornsen 2008, Brudvig 2010). Future research that identifies specific characteristics such as threshold levels of evergreen oak encroachment that would impede reintroduction of fire due to decline in fine fuels would permit managers to be targeted in their application of other more expensive treatments, such as mechanical removal or herbicide.

5.3 Implementation

Dynamic reference model

Even though the importance of changes in assemblages and ecological functions over time is conceptually inherent in restoration trajectories, in practice, few studies have quantitatively addressed such changes. To our knowledge, we present one of the first applications of a robust multivariate statistical technique to measure plant community changes in restored sites relative to the dynamic reference sites over a 15 year period (see 5.7.1). The long term observations presented here are not only unique, but illustrate how incorporating longer-term temporal variation into the envelope that defines reference target ecosystems is essential in measuring management success. We demonstrate a unique approach that has direct application and relevance to a wide range of restoration projects, particularly where comparisons of recovery trajectories due to initial restoration treatments is of interest. By incorporating the dynamic nature of reference conditions in a changing and unpredictable environment, our approach avoids a rigid guideline for projecting desired restoration goals. Another far reaching application of this approach is in situations where restoration of a particular target community composition becomes unattainable. For example, where legacies or prevailing conditions create an ecological threshold, further management intervention may be required. Likewise, recognition of the need to reexamine restoration objectives might occur in situations in which habitat for endangered species is a priority objective. Present management for endangered species defines an optimum habitat that is static; however, managing for an optimum endpoint may no longer be possible due to climate change rendering conservation goals for targeted community structure or composition infeasible. Using this assessment tool, constraints to the desired restoration trajectories that cannot be overcome through time may be identified and goals can be accordingly modified.

Moreover, a better understanding of the outcomes of extremely challenging restoration situations can be obtained from use of the dynamic reference approach described here. It is particularly applicable in situations where novel conditions prevail such that no analog reference conditions are present. In such settings, where natural disturbances or loss of foundation species have precipitated major reorganizations of energy, nutrient cycles, and community assemblages (Hobbs and Harris 2001, Seastedt et al. 2008), restoration trajectories could be assessed against the backdrop of changing communities and ecological functions that develop in response to the novel conditions.

RCW Population Model

The validation exercises described here, using RCW populations in the Sandhills region of North Carolina, MCBCL and Eglin AFB, show that the population model is capable of accurately simulating the complex dispersal and social behaviors that govern RCW populations. Thus, using the RCW population model, users can accurately explore the effects of landscape fragmentation, habitat loss, habitat restoration, recruitment cluster construction, and "no management intervention" on current and future RCW populations in a spatially explicit manner.

The validation exercises also indicate places for continued improvement in model behavior. For example, the social behavior of dispersing birds is more complex than depicted in the model. The RCW population model simulates dispersal in terms of the detection of breeding vacancies, whereas behavioral studies have shown that dispersing birds interact regularly with existing, intact groups in more complex ways rather than just focusing their attention on breeding vacancies (Kesler et al. 2010, Walters et al. 2011). Minor discrepancies between real and simulated dispersal and social dynamics in the RCW population model could be traced to the omission of complex social behavior by dispersing birds in the model, which could account for the model's over-estimation in the number of solitary males (Sandhills population) and under-estimation in the number of breeding females (Figure 44; Figure 45). In addition, RCWs may have a much greater intuitive understanding of the landscape than can be incorporated into this or any model. As a result, the model may limit movement in a way that prevents birds from finding each other or breeding vacancies. Still, the modeling tool depicts social structure quite well, and these minor discrepancies have little or no effect on the most critical projections of the model, such as population size and territory occupancy. Thus we do not view this as an important deficiency and would argue that our somewhat simplified model is preferable over a possibly overly parameterized one that would result from attempting to add more complex details of social behavior.

Of more concern is the fact that the RCW population model is overly conservative in its depiction of RCW habitat requirements. Actual population growth, in terms of the number of occupied territories, was greater in the real data for all three study populations, and the model was overly conservative in estimating the success of recruitment clusters (data not shown). Many recruitment clusters that were occupied in the observed populations were rejected by the model due to insufficient habitat unless this feature was turned off in the model (a new option in version 2.0). The model was also overly conservative in predicting budding for similar reasons, especially in areas between existing groups. We conclude that RCW groups can persist on fewer acres of suitable habitat or on acres that do not meet the suitability criteria required in the model. This suggests that the USFWS foraging habitat requirements for the species on which our suitability criteria were based are overly conservative. However, given the great concern over extirpation of RCW populations due to the species' endangered status, it is better to be overly conservative in projecting population behavior than overly optimistic.

In addition, several important assumptions were made in the development of the RCW population model, including (1) a lack of genetic structure, (2) static habitat conditions, (3) no impact of habitat conditions on survival or reproduction, and (4) no immigration. Most notably, the model assumes that habitat does not change over the course of a simulation, except for the aging of pines, and that vital rates (e.g., reproduction and survival) are not impacted by habitat type or quality. However, the longleaf pine ecosystem is fire-dependent (Frost 1998), and habitat conditions for RCWs can quickly improve in response to low intensity fires or degrade if fire is

suppressed. Fire-maintained habitat tends to have a sparse midstory and rich herbaceous groundcover, both of which are associated with larger size and greater productivity of RCW groups, compared to the dense hardwood midstory and sparse and/or woody groundcover characteristic of fire-suppressed ecosystems (Hardesty et al. 1997, James et al. 1997, Walters et al. 2002). Prescribed fire and other management techniques that reduce the hardwood midstory in longleaf pine communities are frequently used as restoration tools that can convert unsuitable habitat to suitable habitat over a relatively short time period (Provencher et al. 2001b, Provencher et al. 2002b, Provencher et al. 2002c). The RCW data we used for validation purposes was from a period characterized by widespread habitat improvement through these techniques on all study areas. On the other hand, the parameter estimates used in the model were based on a prior period when habitat was generally in poorer condition. We suggest that the model's inability to track abrupt changes in certain population variables (e.g., population size, number of occupied territories, number of solitary males; Figure 44; Figure 45; Figure 46) could be due in part to the fact that habitat changes in the real landscape, which could not be accounted for in the population model, had impacts on the actual RCW populations but not the simulated one. Model performance likely could be improved if the effects of changes in landcover and habitat quality on RCW demography could be incorporated, a capability we ultimately developed in the RCW DSS.

Thus, a major focus of this Project was to improve how habitat is modeled in projections of RCW population dynamics. Specifically, we developed a state and transition model of longleaf pine dynamics in the generic platform ST-SIM (Daniel and Frid 2011) so that the landscape can change over the course of a simulation in response to events such as fires and management actions. By linking a landscape model with the population model in what we refer to as the RCW DSS, we were able to simulate the impacts of natural landscape change and succession in conjunction with potential management actions on RCW population persistence and growth. This improved functionality would allow managers to evaluate how the management of forest, future landuse changes, and improvements or reductions in habitat quality would impact RCW populations.

ST-SIM model

Based on validation results described in Section 4.3, we maintain that the ST-SIM model that we developed to represent the current landscape states, natural transitions, and management regimes is an accurate representation of the longleaf pine ecosystem at Eglin AFB. Although we found a significant difference between the landcover state area distributions in the reference and predicted landcover maps, we assert that the inaccuracies were largely the result of misclassified landcover types in the reference datasets. In addition, the ST-SIM model was still able to capture approximate trends in landcover dynamics and had a relatively high level of spatial accuracy according to the spatially explicit analysis. Furthermore, even if the model did not make accurate quantitative predictions of landcover distribution, models like the ST-SIM landscape model for Eglin AFB can still act as important tools for evaluating the relative impacts of development projects, ecosystem management activities, and other forms of landcover change through time (Beissinger and Westphal 1998, Crone et al. 2011).

RCW DSS

The results of the scenarios described in Section 4.4 show that (*i*) the RCW DSS version 3.0 is capable of accurately predicting RCW dynamics and that (*ii*) considering changes in

habitat suitability is an important component of the model framework. For the relatively short simulation described (13 years), we also found that the results of the Foraging Constraints and Habitat Suitability Constraints scenarios did not differ substantially, and the predictions of both scenarios did not differ significantly from the observed population. Therefore, because the processing time and memory requirements are extremely high for simulations using the Habitat Constraints landscape option, we recommend that users consider selecting the Foraging Constraints landscape option for shorter simulations, for simulations where habitat suitability does not change dramatically through time, or for simulations where landscape management options are not being evaluated and compared. However, because the No Constraints scenario substantially overestimated the number of occupied territories, we stress that the user continues to employ either suitability- or area-based constraints in simulations of RCW population dynamics.

We also maintain that our use of a landscape-population metamodel as opposed to a "megamodel" (Lacy et al. 2013), in which all aspects of the system are contained within a single, highly complex model (e.g., Willis and Bhagwat 2009, Purves et al. 2013), has important benefits for better understanding RCW vulnerability to landscape-mediated threats and sensitivity to proposed management applications. Interacting but independent models can more easily provide insights into how each process impacts the system in isolation while also elucidating if synergisms in those processes have cumulative impacts that differ from those due to individual processes (Nicholson et al. 2002, Lacy et al. 2013). For example, Brook et al. (2008) describe how species are often driven to extinction by multiple threats that interact in amplifying feedbacks, highlighting the importance of understanding both the mechanisms underlying each individual threat (Lawler et al. 2002) and interactions among those threats (Brook et al. 2008). For the RCW DSS specifically, this metamodel approach will allow base managers to understand, for example, (*i*) how multiple types of changes to the landscape (e.g., development projects, changes to fire regimes, etc.) impact the amount and location of suitable RCW habitat (i.e., ST-SIM landscape model results alone) and (*ii*) if that change in habitat suitability is enough to impact RCW population trends (i.e., results of RCW population model). Furthermore, by altering landscape parameters associated with each threat in isolation (e.g., increasing the amount of habitat lost to development <u>or</u> reducing the amount of longleaf pine burned each year), a user will also be able to examine (*i*) how the response variable for the landscape model changes (e.g., area of suitable habitat) and then (*ii*) how the change in that response variable ultimately influences the final response variable (e.g., the number of RCW breeding pairs). These steps can then be repeated after modifying the initial landscape variables in pairs and all together to ultimately understand how interacting threats impact this federally endangered species. Although potentially possible, manipulating and understanding pathways for how individual input variables (or threats) impact the overall model output (or RCW population) would be difficult within a more complex megamodel.

A metamodel also allows for the connection of models that operate over different spatiotemporal scales, facilitating the analysis of effects that cross those scales (Lacy et al. 2013). For instance, changes on the longleaf pine ecosystem at Eglin AFB may only be visible over longer temporal scales or at greater spatial resolutions. The RCW population model, in contrast, simulates RCW habitat availability at a finer spatiotemporal grain (~ 1 year intervals, 70+ acre territories). The metamodel approach allows for these models to be linked by not requiring a single, common time frame or spatial resolution. It will also allow users to

understand if there are time lags in how long-term changes in the landscape influence RCW populations as projections are extended through time.

Combining these models in a metamodel approach also allows for flexibility in which models are being connected. For instance, ST-SIM landscape models developed for other military installations with RCWs (e.g., MCBCL, Fort Bragg) could be connected to the RCW population model to simulate site-specific trends in RCW populations. This work is currently in development by the report authors under DCERP RC-2245. The landscape model could also be connected to population models for other native species with similar habitat needs.

Finally, metamodels provide a framework that is as much social as it is technical by allowing individuals across multiple disciplines to integrate knowledge and ideas in a manner that provides a comprehensive representation of a complex system. For example, the development and use of the RCW DSS has and will continue to bring together scientists and natural resource managers from a broad range of areas of expertise, including landscape ecology, restoration ecology, conservation biology, RCW and longleaf pine biology, natural resource management and many other areas. In a metamodel approach, individuals are able to contribute to the model that reflects his/her area of expertise (resulting in a strong discipline- or component-specific model) while the metamodel framework provides a means of communication across the disciplines to provide a stronger representation of the full system.

Programming Issues

In Sections 4.2 and 4.3 of this report, we established that the RCW population model (version 2.0, operating under nesting and foraging area constraints) and the ST-SIM landscape model offer predictions of RCW population and longleaf pine ecosystem dynamics, respectively, that do not deviate significantly from observed dynamics. Therefore, each model alone provides a robust representation of the target systems, and both models can be used as trusted tools by base natural resource managers.

Similarly, in Section 4.4 we established that the predictions of the RCW DSS, which links the RCW population model version 3.0 (operating under Habitat Suitability Constraints) and the ST-SIM landscape model, did not significantly deviate from observations, at least over shorter time periods. However, as described in Section 4.5, a programming issue currently prevents us from employing the RCW DSS to make predictions over longer time periods when the Habitat Suitability Constraints landscape option is utilized. Before publishing any results generated by this research project, we will work to rectify this programming error.

Beyond this particular programming error, we faced several operational problems in the final year of this research project. In the update from ArcGIS version 9.3 to 10.0 to 10.2, ESRI made major coding changes that had devastating consequences for the RCW population model, which operates as a toolbar embedded in ArcGIS. We were able to return functionality to the model, but the RCW population model only operates in ArcGIS 10.0 at this time. Therefore, the RCW population model is currently operational; however, users will need to operate the toolbar within ArcGIS 10.0 indefinitely. Further upgrades to the RCW population model that would make it operational in updated versions of ArcGIS software are beyond the funding and time limitations of this study, and we do not plan to make these upgrades at this time.

In returning functionality to the RCW population model in ArcGIS 10.0, numerous programming bugs were introduced to the RCW population model that took months of work to uncover, understand, and fix. Currently, all bugs have been fixed, with the exception of the budding error uncovered as part of modeling described in Sections 3.5 and 4.5. Furthermore, we

are working with our programmer at this time to rectify this budding error. As of June 2015, the error appears to have been resolved, and we are in the process of testing the model's predictions. When we are satisfied with the accuracy of the model's predictions, we will re-run all scenarios described in this report and will include these updated results in future publications.

However, these efforts showed us that the coding language that currently provides the basis for the population model is terminally outdated, which makes the model in its current form unstable and prone to error. Additional bugs or errors that we are not aware of at this time may arise in the future, and we plan to work with any users who encounter such problems to the degree possible to maintain the operability of the RCW population model.

Despite these issues, we have established in Section 4.5 that the RCW DSS can still be used by natural resource managers to predict RCW population dynamics following changes to landscape conditions. Managers can do so using a more static version of the RCW population model, operating it under Nesting and Foraging Area Constraints with an initial landscape layer representing future conditions as predicted by the ST-SIM landscape model.

We will continue to develop the ST-SIM landscape model and the RCW population model for use at other locations, such as MCBCL and Fort Bragg, as part of DCERP project RC-2245. This work will largely require alterations of the ST-Sim landscape model to better reflect the longleaf pine ecosystem dynamics at these additional military installations. This work is currently in progress.

Recommendations for technology transfer

Natural resource management programs often rely on field as well as spatial data to monitor a focal ecosystem over time and across large geographic areas. Some programs may use only field data while others may use both plot and spatial data. Using examples from Eglin AFB, the following section describes different approaches for how field and spatial data can be used to assess ecosystem condition over time. The next section recommends how these two components, field and spatial assessments, could be integrated in a DSS to facilitate the assessment of an ecosystem's movement over time and toward desired conditions in an uncertain and dynamic future. Utilizing both local field data and large-scale spatial data to monitor a focal ecosystem provides a comprehensive picture of condition over time and across a large landscape to inform future management activities. In addition, exploring the similarities and differences in the information from plot data and remotely-sensed data provides a greater understanding of how to monitor and model an ecosystem, the dynamics of the system, and how the ecosystem responds to management efforts and anthropogenic disturbances.

The following section provides more details on the steps in the workflow shown in Figure 51 for using both the plot and landscape scale assessments to monitor change in a DSS that will allow managers to better understand how management actions are changing conditions across the landscape in an uncertain future.

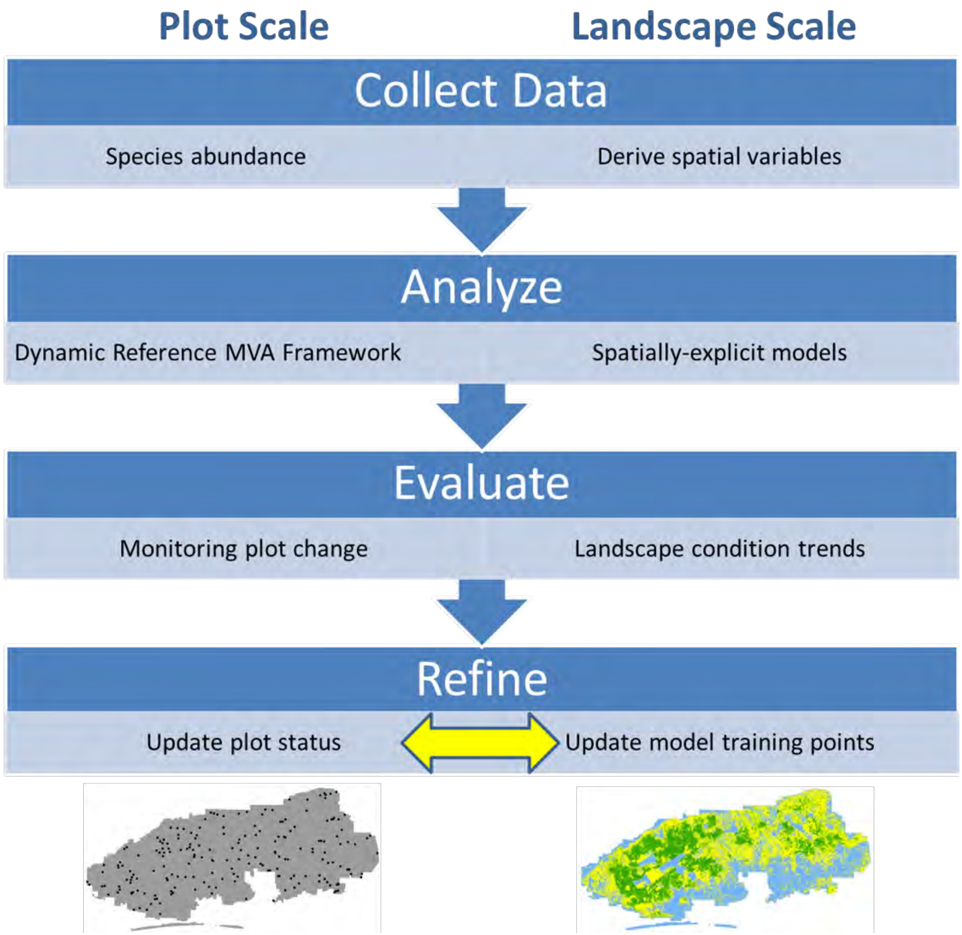


Figure 51. Workflow schematic illustrating the plot and landscape-scale level assessments of longleaf pine sandhills at Eglin AFB and how they are integrated in a DSS.

Plot-scale assessment

Multivariate Analysis (MVA) of monitoring data to assess change in species composition over time and in response to management efforts is critical when relying on plot data to assess ecological trajectories. Eglin AFB Dynamic Reference MVA Framework (Hiers et al. 2012, Kirkman et al. 2013) is the preferred methodology developed in this study. Vegetation data collected at Eglin AFB's long-term monitoring plots from 2001 to the current year is analyzed in a multivariate framework using NMDS ordination with Mahalanobis Distance (MD) to measure plot movement in species compositional space over time and in relation to other plots. The purpose of these analyses is to better understand and quantify the trajectory of longleaf pine communities in response to management activities intended to restore degraded longleaf pine habitat and maintain high quality habitat across the installation. This information can help evaluate the effectiveness of longleaf pine management actions in reaching restoration goals for this ecosystem, highlight the dynamic nature of longleaf pine communities, and inform future management activities at Eglin.

Limitations/caveats

This approach requires a long-term field monitoring program that samples plots on a regular timeframe and in response to management actions and disturbances. In addition, the multivariate framework used at Eglin AFB requires the identification of initial reference sites in order to evaluate how restoration plots are moving in relation to reference plots as well as to understand how reference areas are changing under new environmental conditions such as those expected and already occurring due to climate change. While the analyses use a statistical approach to help bound the range of variability within reference and restoration sites, the approach is dependent on the sites identified as reference. Determining what constitutes reference sites is a challenging task as there are often few suitable sites remaining, expert opinion is often biased and subject to disagreement, and it is difficult and likely not useful to try to return to a pre-Columbian landscape ideal (Hiers et al. 2012). The need to compile field data, collect ancillary management data, QA/QC large datasets, run relatively complex multivariate analyses at a regular interval, and interpret the results can be another barrier to implementing this type of approach.

Recommendations

Given the limitations and caveats described above, it is critical that multiple methods, such as the multiple expert surveys and spatially-explicit models used at Eglin, are used to identify reference sites (Hiers et al. 2012). The ability to automate the input of field data into a standardized database with QA/QC is an important step to overcome the data-based barriers previously described. Eglin AFB has created such a system through an Oracle-driven web-based DSS. In addition to facilitating the processing of the field data, the DSS automatically generates standardized and accessible reports that allow managers to readily understand the impact of their actions and to determine their next course of action. As the approach relies on the set of reference sites and non-reference sites, it is critical to track plot status each year and update plot status as needed. Finally, multivariate analyses reduce a complex dataset into interpretable patterns, but the results are from a statistical model and any odd findings should always be verified in the field to ensure that data input or analysis errors are not responsible for these oddities.

Landscape-scale condition assessment

Field-based monitoring provides invaluable and detailed information on species composition and structure and how it changes in response to management actions and disturbances such as hurricanes and drought. Spatial data can help integrate and augment this localized plot information to provide a representation of condition across a large geographic area at a particular time. A spatially-explicit assessment of ecosystem condition gives managers the ability to understand large-scale trends and to help direct action to specific places on the ground that might otherwise be missed in a large landscape. Similar to field-based data, spatially derived data inputs can be updated on a regular basis to help track change in condition over time.

Approach 1: Expert-Based Model

Example: Eglin AFB Ecological Condition Model (ECM)

Eglin AFB developed a spatially explicit expert model, the ECM, to assess the structural and compositional condition of longleaf pine sandhills across the approximately 500,000 acre installation. The model was developed by combining current science on longleaf pine systems with the experience of natural resource managers and translating this knowledge into a GIS

framework (Wiens et al., 2009). The model is currently run on an annual basis in PCI with ten model inputs derived from satellite imagery and vector data. The model assigns each pixel across the landscape an ecological condition Tier score from one to four. Tier 1 represents the highest quality longleaf pine habitat while Tier 4 reflects the most degraded areas. The model results are aggregated to 1-ha hexagonal units to inform management priorities across the base.

Approach 2: Statistical/Machine-learning Models
Example: Eglin AFB Maxent Model

As an additional source of information about longleaf pine condition across Eglin, maximum entropy modeling, implemented with Maxent software, is used to develop a predictive model of high quality (Tier 1) longleaf habitat across Eglin AFB. Maxent uses a machine learning approach to predict the likelihood of a pixel containing the species or other occurrence of interest based on the values of predictor variables and occurrence localities. For the Eglin Maxent model, the predictor variables are the same spatial inputs as those used in the ECM. The training samples are points randomly drawn from monitoring plots that currently contain high quality longleaf pine habitat (i.e., reference plots) across the AFB. Maxent also has the ability to apply model parameters to spatial data from previous and/or future years through the projection feature. At Eglin, an initial model was developed using the 2011 predictor variables and the training samples. K-fold cross-validation was used to build the model from a set of replicated model runs for 2011. The average prediction from the ten runs was used as the final output. The average ten percentile training value was used to threshold the logistic output into a binary grid of Tier 1 habitat and all other habitat. The ten percentile training presence omits the ten percent of training data with the lowest likelihood of occurrence. To apply the 2011 model parameters to data from 2012-2013, the projection feature in Maxent was used. The projection feature enables application of model results from one set of predictor variables to another set. When projecting to another dataset, Maxent identifies variables for which the range of values is outside those used in the baseline (2011) time period. If there is variation, the model results should be interpreted with caution.

Approach 3: Ensemble of Statistical Models
Example: Eglin AFB Ensemble Modeling (currently in testing phase)

Ensemble modeling or ensemble forecasting can be implemented for species distribution mapping methods such as Maxent, enabling the treatment of a range of methodological uncertainties in multiple models and the examination of species-environment relationships. The Eglin ensemble modeling is implemented in R (R Development Core Team 2013) with a package called *biomod2* (Thuiller 2009). It includes the ability to model species distributions with several different techniques, test models with a wide range of approaches, and project species distributions into different environmental conditions. Ensemble modeling was used to build additional habitat suitability models to supplement the maximum entropy and ECM models traditionally generated as part of Eglin AFB's monitoring effort. Four of the most widely-used, easily-implemented and interpretable models were used. These models included the generalized linear model (GLM), the classification tree analysis (CTA), the random forest model (RF), and the surface range envelope (SRE), also known as BIOCLIM (SRE). The initial results of the Eglin ensemble model show areas of Tier 1 predicted by all the models as well as areas where all or some of the models disagree. The combination of different models provides a more robust and reliable prediction of current Tier 1 longleaf pine habitat, and can target site investigations to

those areas where the models do not agree which can help users better understand the role of model inputs and parameters.

Limitations/caveats

The predictive models described above are models and should be interpreted as such. The results of Eglin's predictive habitat models should be considered an approximate estimate of the likelihood of high quality longleaf pine occurring in a particular area. For the statistical models (e.g., Maxent, ensemble), there is much debate in the literature concerning how to threshold species distribution models. While the use of the ten percentile training threshold has been common in recent Maxent applications, it is only one of many approaches to threshold prediction surfaces. The use of variables derived from imagery and the location of the training points themselves are other potential sources of error. Anomalies in the input data can be magnified in the results. While the training points were randomly generated within 1-ha plot hexagons and the large reference blocks, the points are likely spatially autocorrelated which means that samples drawn for the 10-fold cross-validation are likely not independent and could result in inflated are under curve (AUC)values (Veloz 2009). That said, it has also been shown that cross-validation tends to result in more realistic AUC values than simply using a single model run. When running the Maxent and ensemble modeling projection feature, care should be taken in determining the appropriate training points to use. As the training points are reference sites identified through field-based surveys and MVA of monitoring data, current areas may not have been indicative of reference conditions in previous years. It could be a challenge to run this type of analysis backward because areas selected as reference sites in the current year may not have been reference when the imagery used to derive the older spatial data inputs was developed. However, if documentation of plot status over time is available, then the training points could be modified as needed for a particular time frame. These and other considerations inherent in the use of predictive models reiterate the importance of carefully using the results from Maxent, ECM, or any other predictive model to provide a general picture, rather than an exact account, of change in longleaf pine condition over time.

Recommendations

The following are recommendations when using expert-driven spatially-explicit models and/or statistical models. In both types of models, it is important to assess the sensitivity of the results to changes in the weights of the input variables (Chen et al. 2010). For Eglin's ECM, a sensitivity analysis conducted in 2011 found that the high condition scores were least sensitive to changes in the input weights while the lowest condition classes were more sensitive. Further, no pixels moved more than one Tier score from the original baseline Tier score with up to a 20% change in the model weights. For species distribution models such as Maxent, it is important to understand the sensitivity of the model results to changes in the model parameters, input variables, and perhaps most importantly, threshold selection. In addition, for all analyses, it is critical to review the spatially-explicit input data as anomalies in the inputs will be propagated throughout the results. Comparing current model inputs with previous year's inputs can help identify areas that experienced change beyond what might be reasonably expected. With Maxent, care must be taken when projecting a model onto new data. As with the identification of reference sites, the use of a single model may not provide a complete explanation of the relationships between ecosystem condition and the explanatory variables. Each model within Eglin's ensemble approach has strengths and weaknesses that can be difficult to interpret, and

ensemble modeling allows researchers and managers to observe the variability within the different model projections. By observing the variability between models, managers can be conservative with habitat estimates that inform management decisions. With one model alone, this important variability may not be detected. They can also prioritize areas that exhibit higher confidence through greater model agreement and further investigate those areas of incongruence. Finally, as described in the *Limitations* section, perhaps the most important point to remember is that the results are from a model and should be interpreted as an estimate not an actual account of change in landscape condition over time.

6. Workshop for Managers

6.1 Workshop summary

Individuals from land-managing agencies and organizations in the Southeast U.S. attended a workshop in 2014 to discuss the integration of an "Uncertain Future" (e.g., climate change, invasive species, land use changes, economic changes) into the management and restoration of conservation lands. The workshop was held from March 24 to March 26 at the Joseph W. Jones Ecological Research Center (Ichauway) in Newton GA. This workshop was a product of a large scale research project funded by the U.S. DOD, SERDP, titled ***Developing Dynamic Reference Models and a Decision Support Framework for Southeastern Ecosystems*** (SERDP RC-1696). The workshop for land managers and planners followed a conference organized by the Jones Center and collaborators titled "*Conservation and Natural Resources Management in an Uncertain Future: Using the Southeastern U.S. as a Model for Managing Change*".

The Uncertain Future Workshop brought together twenty-one individuals from a wide-range of land-managing agencies and organizations, including the National Park Service, USFWS, U.S. Forest Service, Eglin AFB, Georgia Department of Natural Resources (GA DNR), Florida Natural Areas Inventory, TNC, Longleaf Alliance, Jones Ecological Research Center, and Archbold Biological Station.

The purpose of the workshop was to introduce a broad audience of land managers and planners to the concepts of an Uncertain Future and Dynamic Reference Conditions and incorporating the idea of managing novel ecosystems. The focal activities of the workshop were organized around the following questions:

- What is the concept of an "Uncertain Future" in relation to the conservation of natural resources?
- What barriers exist to integrating this concept into conservation management and restoration?
- What solutions exist for incorporating an “Uncertain Future” into conservation management and restoration?

The objectives of the workshop were to:

- Identify strategies for integration an "Uncertain Future" into conservation management and restoration planning.
- Produce a document summarizing the key concepts and strategies that emerged from workshop discussions (white paper and/or a publishable manuscript).

The first third of the workshop consisted of a series of invited presentations; structured to introduce participants to examples of the complexities associated with managing conservation lands in a changing and unpredictable environment. The presentations also highlighted recent research funded by the SERDP grant, including:

> Kirkman K. K., Barnett A. B., Williams, B. W., Kiers, J. K., Pokswinski, S. M., & Mitchell, R. J. 2013. A dynamic reference model: a framework for assessing biodiversity restoration goals in a fire-dependent ecosystem. *Ecological Applications* 23:1574-1587.
>
> Hiers J. K., Mitchell, R. J., Barnett, A. B., Walters, J. R., Mack, M., Williams, B. & Sutter R. 2012. The dynamic reference concept: measuring restoration success in a rapidly changing no-analogue future. *Ecological Restoration* 30:27-36.

In addition to these two papers, the following articles were sent to participants before the meeting.

Anderson, M. G., & Ferree, C. E. 2010. Conserving the stage: climate change and the geophysical underpinnings of species diversity. *PLoS One* 5(7): e11554.

Hobbs, R. J., et al. 2006. Novel ecosystems: theoretical and management aspects of the new ecological world order. *Global ecology and biogeography* 15(1):1-7.

Jackson, S. T., & Hobbs, R. J. 2009. Ecological restoration in the light of ecological history. *Science* 325(5940): 567.

Ross, M. S., O'Brien, J. J., Ford, R. G., Zhang, K., & Morkill, A. 2008. Disturbance and the rising tide: the challenge of biodiversity management on low-island ecosystems. *Frontiers in Ecology and the Environment* 7(9):471-478.

Seastedt, T. R., Hobbs, R. J., & Suding, K. N. 2008. Management of novel ecosystems: are novel approaches required? *Frontiers in Ecology and the Environment* 6(10): 547-553.

Stoddard, J. L., Larsen, D. P., Hawkins, C. P., Johnson, R. K., & Norris, R. H. 2006. Setting expectations for the ecological condition of streams: the concept of reference condition. *Ecological Applications* 16(4):1267-1276.

In the remainder of the workshop, small group and whole group discussions addressed the issues of hurdles and identified solutions to promoting integration of the idea of an uncertain future into conservation management and restoration planning. The hurdles identified included:

- Uncertainty identifying management goals
- Institutional inflexibility
- Accept the management of novel ecosystems
- Manage for resilience

Potential solutions and steps forward were discussed for each of these hurdles. Participants completed a questionnaire at the end of the workshop to describe the relevance of the topics of the workshop in relation to their work environment. The organizers of the workshop, all of which worked on other project components, included: Analie Barnett, TNC; Kevin Hiers, Eglin AFB; Kay Kirkman, Jones Ecological Research Center; and Rob Sutter, Enduring Conservation Outcomes.

6.2 Presentations

An Introduction to an Uncertain Future (Rob Sutter)

The question "How can we better manage and restore conservation lands for an uncertain future?" is being addressed by many ecologists and conservationists.

This uncertain future is predominantly driven by climate change, but also includes many other anthropogenic environmental changes such as nitrogen deposition, land conversion, population shifts, invasive species, altered fire regimes, and increasing soil salinity. These drivers of change will result in a mix of novel ecosystems consisting of non-historical species configurations and ecological functions.

There is a developing literature and dialogue on the topic. Recently, the Jones Center and collaborators hosted a workshop last November titled *"Conservation and Natural Resources Management in an Uncertain Future: Using the Southeastern U.S. as a Model for Managing Change"*. The conference speakers included Dr. Emily Bernhardt (Duke University), Dr. Jerry Franklin (University of Washington), Laurie Fowler (University of Georgia), Dr. Richard Hobbs (University of Western Australia), Dr. Stephen Jackson (U.S. Geological Survey), Dr. Gene Likens (University of Connecticut), and Dr. David Lindenmayer (Australian National University).

"The future ain't what it used to be" is a quote from Yogi Berra, former catcher and manager of the New York Yankees. It is true: the future is arriving faster, the future affects a larger spatial extent, and the future may be worse than predicted. There is accelerating climate change, rising sea levels, increasing human population numbers, a future where large populations will shift to other locations.

This workshop will address the opening question. Our outcomes will focus on how we, as land managers, can integrate an uncertain future into current management and restoration. The presentations in the morning and afternoon provide examples of current and future novel ecosystems, and how the management of these systems is being approached. They are not meant to be comprehensive, but to generate thoughtful discussions during the rest of the workshop.

The River of Fire: Managing Fire in the Modern Everglades (Rick Anderson)

The Everglades National Park (National Park Service), in south Florida, is one of the most visible and expensive restoration projects in the world. The majority of the Everglades ecosystems are significantly altered from historic conditions, primarily the result of engineered drainage for industrial-scale agriculture and urban development. Many of these systems will continue to change with sea level rise (SLR), altered fire regimes, influence of non-native species, and changes in hydrology creating a quintessential novel ecosystem. In the post-drainage everglades, organic soils and fire sensitive tree islands were impacted by severe and historically rare events contributing to the development of novel native and non-native vegetation assemblages. The landscape dissected by canal and roads constrain landscape level fire events common before large-scale human alteration. Invasive plant and animal species are a significant threat in natural communities with new exotic species introduced at an unprecedented

rate. Other systems thought to be natural were greatly influenced by pre-settlement land use. A major obstacle impeding adaptive management in the context of changing environmental conditions relates to conflicting objectives for the mix of natural and novel ecosystems, including federally listed species. Presently the fire induced restoration management activities for the Everglades lack achievable goals and objectives that recognize the novel condition of this ecosystem and fails to set desired conditions based on sustainable ecological function and ecosystem services.

Sea Level Rise and the Change in Coastal Habitats (Jason Lee)

The GA DNR is prioritizing coastal habitats that will require management and mitigation in response to SLR. Models of SLR and the response of ecological systems have high levels of uncertainty. Georgia's shoreline is dominated by Pleistocene bluffs which offer limited area for marshes and beaches to migrate. Other inland areas have substantial upland and river habitat for marsh migration, especially in river corridors and areas with extensive accretion, but have other natural and anthropogenic barriers. Recent extreme high tides are an early indicator of SLR, and their increased occurrence is affecting the reproduction of shorebirds and sea turtles. Dredge spoils are an example of a novel ecosystem that will be a primary management option for shorebird nesting.

Human Water Consumption and Stream Flows in the Lower Flint River Basin: Past and Future Trends and Environmental Consequences (Paul McCormick, Steve Golladay, Woody Hicks)

The natural flow regimes of the Lower Flint River and its tributaries in southwestern Georgia have been altered by the use of groundwater and surface water for local agricultural irrigation and by the increase of the human population in the upper reaches of the watershed. In particular, stream flows during recent droughts have been as much as 20-fold lower than those during the historic drought of record (1950s), and many stream reaches that were historically perennial now experience periods without flow due to agricultural water consumption during droughts. These trends have implications both for future human water use and for stream-dependent fauna, including endangered species. Extreme low flows disproportionately affects key ecological habitats such as shoals and snags and leads to habitat fragmentation in some stream reaches. Reduced water quality (e.g., low dissolved oxygen) during these events also may negatively affect some biota. Beyond an indefinite moratorium on new agricultural water permits, proposed remedies to this issue have focused on technological solutions such as increased water use efficiency and water-storage infrastructure such as surface water reservoirs and aquifer storage and recovery. These and other solutions may be decreed by changes in state water policy or by legal rulings in federal courts. An important first step for natural resource managers is to articulate explicit priorities for conservation such as endangered mussels, fisheries, and/or ecosystem function.

Building Resilience to Sea-level Rise on the Albemarle-Pamlico Peninsula (Christine Pickens)

The Albermarle-Pamlico Peninsula, in eastern North Carolina, is a low lying area averaging 1.5 feet above sea level. The primary vegetation is pocosin, a shrub dominated system that occurs on shallow and deep peat soils. The area has been extensively ditched in the past for forestry, agriculture, and a military facility. The ditches are a major threat to the ecosystem,

being a conduit of saltwater intrusion during storm events and higher sea levels. The ditches have also reduced the regional ground water, drying out the vegetation and leading to catastrophic fire events. To protect the pocosins and other freshwater wetlands from drought and catastrophic fire, water management plans have been developed, using structures to increase the water table in specified zones. The goal is to protect these freshwater wetlands as long as possible from salt water and catastrophic fire.

Resilient Landscapes: Ecological and Conservation Restraints and Opportunities in the Southeast (Analie Barnett)

TNC recently completed an assessment of landscape resilience in the Southeastern U.S. Resilience was defined as the capacity of a site to adapt to climate change while maintaining species diversity and ecological function. The region's landscape was classified into 35 distinct geophysical settings based on the combination of an elevation zone and a bedrock or surficial geology type. To assess the resilience of each geophysical setting within its respective ecoregion, two factors were examined. The first, landscape diversity, refers to the number of microhabitats and climatic gradients available in an area. Landscape diversity was measured by determining the variety of landforms, the elevation range, and the density of wetlands present in a 100-acre area. The second factor was local connectedness which measures how movement through the local landscape is facilitated or impeded by the surrounding land cover. The method used to assess local connectedness for the region was resistant kernel analysis, developed and run by Brad Compton using software developed by the UMASS CAPS program (Compton et al. 2007, http://www.umasscaps.org/). Landscape diversity and local connectedness scores were combined to identify geophysical settings in the Southeastern U.S. that are expected to be most resilient to climate change and to maintain high levels of biodiversity.

Dynamic Reference Condition Concept (Kevin Hiers)

Traditional ecological restoration is dependent on a reference condition to define desired conditions. This poses a problem for restoration in an uncertain future: reference conditions are changing in response to climate change, invasive species and local extirpation of species, and changes in ecosystem processes. The challenge is: how does one restore to a moving target? Additionally, the selection of reference sites is difficult, if they are available. Errors include 1) artificially restricting the reference concept too few reference sites, 2) failure to measure change in reference sites over time, and 3) a quixotic attachment to putative past. Reference sites not only reflect historic conditions, but also legacies of past disturbance and different recovery trajectories from disturbance. Eglin AFB is using a dynamic reference concept to assist in the management of the longleaf pine system. The approach: 1) defines reference sites; 2) refines the definition of reference sites through expert assessment, monitoring data, and statistical analysis; and 3) measures change in both reference and restoration sites in response to management. Monitoring change is critical in an uncertain future, and measuring change is not a trivial process. It is recommended that managers replace the word restoration, and its connotation of restoring to a past condition, with the word recovery to capture the desired endpoints as defined by changing conditions.

Fire in an Uncertain Future (Joe O'Brien)

The islands in the Keys and in Florida Bay in south Florida and the native pine forest on Turks and Cacaos provide examples of ecological systems with no current or past analog, given

the drastic alteration in community structure and processes. The upland pine rockland community on the Florida islands, home to many endemic species, depends on fresh water and frequent fire. Storm surges and increasing SLR is killing the upland pines, the canopy in these systems and the source of fine fuels for fire, as well as decreasing available freshwater. Vegetation change has been on combination of ramp (slow gradient of change) and pulses (storm events). These systems are losing any resemblance to historic reference conditions. In the Turks and Cacaos, the introduced pine tortoise beetle resulted in 100% mortality of the native pine forest on the islands, an example of a pulse event. On this island, the scrub vegetation that has come in after the loss of the pine forest has no historic analog. A no-analog future requires a reassessment of future ranges of variation, reconsideration of historic ranges as strict guidelines for reintroduction, and restoration, and the need for rapid and often controversial intervention.

Using Multivariate Analysis to Inform Ecological Management in an Uncertain Future (Analie Barnett)

Ecosystems are complex and their management requires an understanding of the effects of multiple environmental factors and management activities on numerous species simultaneously. Additionally, environmental factors and the effects of management change over time and in response to climate change and other disturbances. Multivariate approaches can be used to examine and identify major patterns in this type of complex ecological data. These approaches generally fall into two categories: (1) classification techniques that group samples based on ecological distance; and (2) ordination techniques that represent sample and species relationships in reduced dimensions, with the (dis)similarity based on the values of multiple variables. A framework using a variety of multivariate techniques was developed to inform the management and restoration of longleaf pine sandhills at Eglin AFB. The framework requires the collection of species data at multiple time steps and in response to management actions. The framework consists of the following three key steps: 1) define reference conditions; 2) refine range of reference conditions; and 3) examine change through time in both reference and restoration sites to measure restoration success. The multivariate framework has been used to help Eglin's managers characterize the variability of reference sites over time and determine which activities are moving restoration sandhills toward reference conditions, when reference conditions themselves are changing.

6.3 Hurdles and solutions to integrating an uncertain future into management and restoration

The participants were divided into two groups to brainstorm and discuss obstacles and solutions to integrating uncertainties of the future into their management and restoration actions. The groups were asked to think about hurdles in the following categories: (1) Planning, (2) Implementation, (3) Institutional Structure, and (4) Policy. The breakout groups identified hurdles on Tuesday afternoon, March 25, and the solution breakout group discussions took place on Wednesday morning, March 26. Each breakout group presented their summaries to the whole group for discussion. The following is a summary of the hurdles and solutions.

Uncertainty of management goals

The uncertainty associated with setting management goals, both for relatively natural systems that will likely change in the future as well as novel ecosystems, was a major hurdle

identified by both groups. An overarching question was: What are the priority management goals for an ecosystem: rarity (species, ecosystems), richness, structure, or ecosystem function?

Hurdles:
For relatively natural systems (ones that are structurally and compositionally similar to historic conditions):

- Can these systems be maintained within an uncertain future? Are these systems resilient to the forces of an uncertain future?
- What resources would be required to maintain them?
- What are the decision criteria for changing management of a site from one based on an historic or current analog to one considered a novel ecosystem.

For novel ecosystems (ones that have no historic analog):

- How are management goals established for novel ecosystems?
- How are novel ecosystems identified and their benefits understood?

Solutions:

- **Establishing management goals is the essential first step for both changing natural systems and novel ecosystems.** In doing so, one should accept that the pre-Columbian goal is no longer the desired condition for management, even for relatively natural systems. Establishing clear goals are even more important with no-analog systems and needs to include more stakeholder involvement. Additionally, managers need to learn how to set objectives for a moving target.

- **Do not set the bar too low.** Don't abandon high quality natural systems because management is difficult and expensive. Don't accept novel ecosystems because they are easier to manage. Conserving high quality areas will provide flexibility for conservation (sources of biodiversity) in the future.

- **A regional approach**. It was noted that many of the ecosystem services, which may be the management goals of novel ecosystems, are not under the control of local land managers. Services such as water quality, ground water and aquifers quantity, and carbon sequestration, are regional issues or need to be addressed at a regional scale.

Institutional inflexibility
Hurdles:
Institutions tend to be very structured and inflexible because of their funding mandates. They tend to be risk-adverse, even in the face of failing actions. Yet the more uncertain the future, the more flexibility is needed. Flexibility is needed in planning, funding, and policy.

Solutions:

- **Accept changing and novel ecosystems as inevitable conditions for ecological systems.** Currently, institutions look at the elements of a novel ecosystem only as being threats, such as invasive species. There is need to identify and understand the implications and value of novel ecosystems.

- **Develop a classification system for novel ecosystems as a way accepting the value of these systems and identifying these systems on the landscape.** A classification system for novel ecosystems would be challenging, given the absence of a reference system and the rapid changes occurring in some ecosystems.

- **Establish threshold criteria for when a relatively natural system shifts to a novel ecosystem** and when institutions should begin planning for novel ecosystems.

- **Modify regulations, policy, and law** to reflect a more dynamic management approach, focused on a no-analog future rather than a pre-Columbian past. Modifying regulations, policy, and law requires extensive education of stakeholders.

Accept the management of novel ecosystems

Hurdle:

Exposure of the concept of management of novel ecosystems is needed for various audiences including the public, institutions, foundations, and local and national conservation organizations, as well as managers is necessary for a change in strategy to be incorporated.

Solutions:

- **Educate stakeholders in the concept and implementation of managing for changing and novel ecosystems.**

Manage for Resilience

Resilience is defined as the capacity of a landscape to maintain native species and ecological function, and can be used for both relatively natural and novel ecosystems.

Hurdles:

- How does one manage for resilience?
- How does one measure the success of managing for resilience?

Solutions:

- **Define resilience by outcomes and conditions.** Resilience can be defined by its outcomes (loss of native species, ecological function) but can also be defined by condition: ecosystem variation, environmental variation, landscape connectivity.

- **Work in regional partnerships.** Managing for resilience at the landscape level will require working in regional partnerships. Current examples approaching this are the America's Longleaf Restoration Initiative and the Coastal Invasive Species Management Area (CISMA). The conservation community needs a few examples of managing a novel landscape for resilience that both meets ecological objectives as well as showing wise use of taxpayer dollars.

- **Combine resilience with novel ecosystems.** Recognize the role of novel ecosystems in providing connections between managed areas and increasing the resilience of the

landscape. Focus research on a few systems to demonstrate the effectiveness of managing for resilience and novel ecosystems.

6.4 Conceptual model

One of the breakout groups developed a conceptual model to capture the decision-making process along a continuum from relatively natural ecosystems to completely novel ecosystems. The vertical scale represents changes in the biotic and abiotic components of a population/habitat or an ecosystem. The sections of the triangle represent the general categories of populations or ecological systems, from relatively natural, defined by their close resemblance to historic ecological systems, to completely novel ecosystems. The text highlights the goal for each section, with the arrow the decision trigger. With time, all ecosystems will move down in the model; representing the concept of inevitable change in the face of climate change, land use, changes in ecological processes, and shift in populations. The value of the model is, in part, to get managers to think about the future and to plan for smooth transitions between the ecological states.

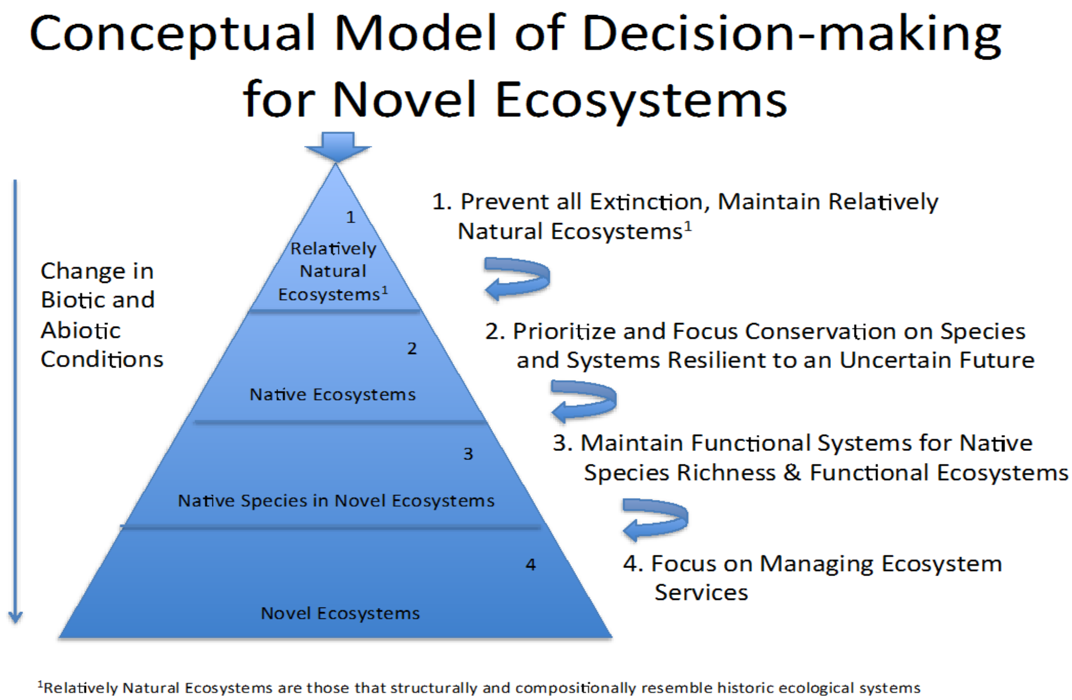


Figure 52. Conceptual model of decision-making for novel ecosystems

6.5 Summary of questionnaire responses

A three-part questionnaire was provided to workshop participants at the end of the workshop asking participants describe the relevance of the topics of the workshop in relation to their work environment.

1. What did you find useful in the presentations and discussions about conservation management with an uncertain future relative to ***your*** work environment?
2. What specific barriers to incorporating long-range planning for an uncertain future exists in ***your*** organization?
3. Evaluate the utility of presenting the topic of an uncertain future to others in ***your*** organization and what would be the best mechanism for communication?

Responses are summarized below, edited for clarity and combining similar feedback.

What did you find useful in the presentations and discussions about conservation management with an uncertain future relative to your work environment?

- An openness to consider objectives outside of the pre-Columbian framework as a responsible and proactive approach rather than surrender
- A hierarchical framework for considering objectives for managing systems in a no-analog future
- An improved ability to articulate concept of variation and change in setting Desired Future Conditions and reference conditions. Provides a framework for discussing best possible/reasonable outcomes.
- A diversity of knowledge, expertise, and points of view
- An improved ability to frame research questions and priorities
- Incorporating invasive species dominated ecosystems as a novel ecosystem
- The need for contingency planning for conservation, considering the "what if" and "expect the unexpected"
- Reinforced the value of adaptive management in conservation
- Clarity on the paradigm shift required for planning for an uncertain future
- Refining and clarifying diffuse concepts such as novel ecosystems and management responses to no-analog futures.

What specific barriers to incorporating long-range planning for an uncertain future exists in your organization?

- Limited resources across a wide range of activities, such as the ability to think about the big picture and plan long range, management, monitoring, data collection, and analysis. Resources are devoted to meeting short-term management needs.
- Lack of reference sites on managed property – would benefit from regional network for planning and reference sites
- A rigid natural community classification system
- Fear of "setting the bar too low" for land managers
- Inability of agency response (slow) to match the changing nature of the ecosystems and threats.
- Lack of recognition that goals and objectives can change
- Timeframe of funding

- Incorporating novel ecosystems as conservation targets
- Ecological and economic data on the ability to manage for resilience and what benefits and trade-offs are involved
- How people define a novel ecosystem
- Planning horizons at all levels of an organization
- Legal mandates that require prioritization of species over the systems and ecological function
- Status quo paradigm and institutional and cultural inertia
- Leadership that is poorly education, risk averse, and lacks vision
- Fear of unleashing the genie form the bottle on accepting extinction as an acceptable consequence even when it appears inevitable

Evaluate the utility of presenting the topic of an uncertain future to others in your organization and what would be the best mechanism for communication?

- This topic would be best received and most effectively delivered at the highest levels of leadership (US Forest Service)
- Webinar for other scientists and managers in our organization
- Follow-up workshop focused on wetland restoration
- Provide models and examples of success in the incorporation of an uncertain future in conservation management and restoration
- Workshop for staff at park unit
- Workshop at military planning meetings
- White paper or published paper on the topic
- Through the Landscape Conservation Cooperatives (LCC)
- Through a defining framework, such as was initiated at the workshop
- Through concrete definitions and examples
- Publications and presentations
- Start soon, it will take some time for these concepts to be accepted

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Appendices

A. List of Scientific Publications and Presentations

A1. Articles in peer-reviewed journals

Hiers, J. K., J. R. Walters, R. J. Mitchell, J. M. Varner, L. M. Conner, L. A. Blanc, and J. Stowe. 2014. Ecological value of retaining pyrophytic oaks in longleaf pine forest. Journal of Wildlife Management 78:383-393.

Jones, K. C, B. K. Rincon, and D. A. Steen. 2010. *Bufo terrestris* (Southern Toad). Predation. Herpetological Review 41:334-335.

Kirkman, L. K., A. Barnett, B. Williams, J. K. Hiers, S. M. Pokswinski, and R. J. Mitchell. 2013. A dynamic reference model: a framework for assessing biodiversity restoration goals in a fire-dependent ecosystem. Ecological Applications 23:1574-1587.

Levoie, M., M. C. Mack, J. K. Hiers, and S. Pokswinski. 2012. The Effect of Restoration Treatments on the Spatial Variability of Soil Processes under Longleaf Pine Trees. Forests 3:591-604.

Levoie, M., M. C. Mack, J. K. Hiers, S. Pokswinski, A. Barnett, and L. Provencher. 2014. Effects of restoration techniques on soil carbon and nitrogen dynamics in Florida longleaf pine (*Pinus palustris*) sandhill forests. Forests 5:498-517.

Steen, D. A., L. L. Smith, and M. A. Bailey. 2010. Suggested modifications to terrestrial box traps for snakes. Herpetological Review 41:320-321.

Steen, D. A., G. G. Sorrell, N. J. Paris, K. J. Paris, D. D. Simpson, and L. L. Smith. 2010. *Heterodon platirhinos* (Eastern Hog-nosed Snake). Predator/prey mass ratio. Herpetological Review 41:365.

Steen, D. A., K. C. Jones, J. B. Jensen, B. K. Rincon, J. C. Godwin, and S. P. Graham. 2011. New amphibian and reptile county records for the Florida panhandle. Herpetological Review 42:576-577.

Steen, D. A., J. A. Stiles, S. H. Stiles, C. Guyer, J. B. Pierce, D. C. Rudolph, and L. L. Smith. 2011. *Regina rigida* (Glossy Crayfish Snake). Terrestrial Movement. Herpetological Review 42:102.

Steen, D. A., M. Baragona, C. J. W. McClure, K. C. Jones, and L. L. Smith. 2012. Demography of a small population of loggerhead musk turtles (*Sternotherus minor*) in Okaloosa County, Florida. Florida Field Naturalist 40:47-55.

Steen, D. A., C. J. W. McClure, L. L. Smith, B. J. Halstead, C. K. Dodd, Jr., W. B. Sutton, J. R. Lee, D. L. Baxley, W. J. Humphries, and C. Guyer. 2013. The effect of coachwhip presence on body size of North American racers suggests competition between these sympatric snakes. Journal of Zoology 289:86-93.

Steen, D. A., C. J. W. McClure, J. C. Brock, D. C. Rudolph, J. B. Pierce, J. R. Lee, W. J. Humphries, B. B. Gregory, W. B. Sutton, L. L. Smith, D. L. Baxley, D. J. Stevenson, and C. Guyer. 2014. Snake co-occurrence patterns are best explained by habitat and hypothesized effects of interspecific interactions. Journal of Animal Ecology 83:286-295.

Steen, D. A., C. J. W. McClure, W. B. Sutton, D. C. Rudolph, J. B. Pierce, J. R. Lee, L. L. Smith, B. B. Gregory, D. L. Baxley, D. J. Stevenson, and C. Guyer. 2014. Copperheads are abundant where kingsnakes are not: relationships between the abundances of a predator and one of their prey. Herpetologica 70:69-76.

Sutter, R., J. K. Hiers, L. K. Kirkman, A. Barnett, and D. Gordon. Integrating and Uncertain Future into Conservation Management and Restoration. **Status: Submitted to Restoration Ecology**

Walters, JR, R McGregor, P Baldassaro, K Convery, J Priddy, and S Zeigler. A spatially explicit, individual-based population model for identifying critical habitat for red-cockaded woodpeckers. **Status: In preparation (ready for submission).**

Zeigler, S., J.K. Hiers, R.J. Mitchell, P. Baldassaro, A. Barrnett, and J.R. Walters. An application of the metamodel approach for the conservation of red-cockaded woodpeckers. **Status: In preparation (early stages)**

Zeigler, S., R. McGRegor, P. Baldassaro, K. Convery, J. Priddy, and J.R. Walters. The impacts of new range construction on a red-cockaded woodpecker population on Fort Benning, Georgia. **Status: In preparation (with coauthors)**

Zeigler, S. and J.R. Walters. In Press. Population models for social species: lessons learned from models of red-cockaded woodpeckers (*Picoides borealis*). *Ecological Applications*. **Status: In Press**

A2. Conference and Seminar Presentations

Steen, D.A. Restoration Ecology of Small Vertebrates in Fire-suppressed Longleaf Pine Forests. Joseph W. Jones Ecological Research Center seminar, Newton, Georgia, November 2011.

Steen, D.A. 2011. Restoration Ecology of Small Vertebrates in Fire-suppressed Longleaf Pine Forests. Dissertation Defense Seminar, Auburn University. Auburn, Alabama, October 2011.

Steen, D.A. Reptile Restoration in Fire-suppressed Longleaf Pine Sandhills. World Congress of Herpetology. Vancouver, British Columbia, August 2012.

Steen, D.A. “Why is that Snake Here? How Habitat, Competition, and Predation Influence Snake Occupancy and Abundance”. Southeast Partners in Amphibian and Reptile Conservation (SEPARC) Annual Meeting, Lake Cumberland State Park, Jamestown, Kentucky, February 2014.

Zeigler, S. Models for conservation: How simulation tools can bridge the gap between science and management for endangered species conservation. Invited seminar for the Department of Biology, University of Toronto, Toronto, Ontario, Canada, July 2013.

Zeigler, S. Models for conservation: How simulation tools can bridge the gap between science and management for endangered species conservation. Invited seminar for the Department of Fish and Wildlife Conservation, Virginia Tech, Blacksburg, Virginia, 2013.

Zeigler, S., J. R. Walters, R. J. Mitchell, and J. K. Hiers. A novel linked landscape - population model to connect systems, disciplines, and stakeholders for the conservation of red-cockaded woodpeckers. 26th International Congress for Conservation Biology, Society for Conservation Biology, Baltimore Maryland, July 2013.

A3. Poster Presentations

Steen, D. A. Wildlife assemblage response to longleaf pine management: year one. Georgia Department of Natural Resources Board of Directors Meeting, Newton, Georgia, December 2009.

Steen, D. A. Wildlife assemblage response to longleaf pine management: year one. Alabama PARC Inaugural Meeting, Andalusia, Alabama, November 2009.

Steen, D. A. Wildlife assemblage response to longleaf pine management: year one. Gopher Tortoise Council Annual Meeting, Gainesville, Florida, October 2009.

Steen, D. A. Developing a decision support framework for sandhill restoration on Eglin Air Force Base. Society for Ecological Restoration, Coastal Plains Chapter, Annual Meeting, Auburn, Alabama, March 2009.

Steen, D. A. Influence of Longleaf Pine restoration on avian assemblages and occupancy of species associated with the native ecosystem. Alabama PARC Annual Meeting, Andalusia, Alabama, November 2010.

Steen, D. A. Influence of Longleaf Pine restoration on avian assemblages and occupancy of species associated with the native ecosystem. Gopher Tortoise Council Annual Meeting, Columbiana, Alabama, October 2010.

Zeigler, S., J. R. Walters, R. J. Mitchell, and J. K. Hiers. A novel linked landscape – demographic model to connect systems, disciplines, and stakeholders for the conservation of red-cockaded woodpeckers. 26th International Congress for Conservation Biology, Baltimore Maryland, July 2013.

A4. Conference, Seminar, and Poster Abstracts

Pokswinski, S. M., and J. K. Hiers. Long-term vegetation dynamics in response to fire surrogates and prescribed burning within longleaf pine sandhills. Eglin Air Force Base (AFB) Strategic Environmental Research Development Program (SERDP) Knowledge Transfer Meeting, Niceville, Florida, October 2011.

Abstract: We resampled an experiment led by The Nature Conservancy from 1993-1998, and reference sandhill sites in an existing monitoring program at Eglin AFB. Early analyses of groundcover vegetation data taken over three years and compared to multi-decadal data are challenging current management assumptions and techniques in sandhills on Eglin AFB. Comparing reference plots in NMDS space over time has shown that these plots are dynamic. Similarly, all plots that were characterized as in restoration phase over the last 15 years have moved towards recovery despite the management treatments that were used. While the use of herbicide to facilitate oak midstory removal gave an initial surge towards recovery, over time other treatments showed similar movement to recovery. Additionally, analysis of pine regeneration following the 1996 mast year showed that oak midstory was the strongest predictor of regeneration success. These findings suggest that the initial benefits that expensive management strategies such as herbicide and mechanical oak removal may not be any better when considering long term management strategies.

Steen, D. A. Long-term effects of fire surrogates and prescribed burning on avian and reptile populations and assemblages within longleaf pine sandhills. Eglin Air Force Base (AFB) Strategic Environmental Research Development Program (SERDP) Knowledge Transfer, Niceville, Florida, October 2011.

Abstract: The once-extensive longleaf pine (*Pinus palustris*) ecosystem of the southeastern United States has been reduced to a fraction of its historic extent. A fire-adapted system, many remaining fragments have been fire-suppressed and invaded by hardwood trees, particularly oaks (*Quercus* spp.). This change in species composition alters the habitat and is to the detriment of wildlife assemblages associated with longleaf pine forests. Fire surrogates and prescribed burning have been suggested as potential management strategies to restore fire-suppressed and hardwood-invaded longleaf pine forests to target conditions; due to the unique effects of fire, it is generally suggested that prescribed burning should follow application of any hardwood removal treatment. To determine whether fire surrogates followed by prescribed burning affected wildlife populations and assemblages, we sampled for birds and reptiles within 20 experimental sites and six reference sites. Experimental sites were initially subjected to either mechanical hardwood removal followed by fire, herbicide application followed by fire, prescribed burning alone, or remained in a fire-suppressed state (i.e., controls). Following initial treatment, all sites experienced over a decade of prescribed burning on an approximately two-year interval. We evaluated the effects of a given treatment by comparison of wildlife populations and assemblages on treatment sites to those on reference sites initially and also after over a decade of prescribed burning. If conditions associated with a given treatment were indistinguishable from those of reference sites, we considered this as evidence that management objectives were met. Over the long-term, application of herbicide followed by prescribed burning was the only method that restored bird assemblages to the reference condition, although species positively associated with longleaf pine in reference condition responded positively to all treatments. Occupancy probabilities for these species on all treatment sites were indistinguishable from those on reference sites by the conclusion of the study. Initially, reptile assemblages within treatment sites treated with prescribed burning alone were most similar to those of reference sites; fire surrogates did not immediately provide an observed benefit. At the conclusion of the study, reptile assemblages at all sites were indistinguishable from those on reference sites except for assemblages on sites treated with herbicide, suggesting herbicide application was relatively

ineffective at restoring reptile assemblages. A mark-recapture study of the six-lined racerunner (*Aspidoscelis sexlineatus*) also identified prescribed burning as effective. Initially, abundances on sites treated with prescribed burning alone, as well as on sites treated with mechanical hardwood removal followed by fire, were comparable to abundances within reference sites. Over time, abundances at all sites were comparable to those on reference sites. Overall, effective restoration of wildlife populations and assemblages in fire-suppressed longleaf pine sandhills was achieved and prescribed burning over approximately a decade was generally sufficient to achieve this result. In general, there was little observed benefit or need to employ fire surrogates prior to prescribed burning.

Steen, D. A. Restoration of Reptile Assemblages in Fire-suppressed Longleaf Pine Sandhills. Alabama Partners in Amphibian and Reptile Conservation (PARC) Annual Meeting. Nauvoo, Alabama, September, 2011.

Abstract: Measuring the effects of ecological restoration on wildlife assemblages requires study on broad temporal and spatial scales. Longleaf pine, *Pinus palustris*, forests are imperiled due to fire suppression and subsequent invasion by hardwood trees. We employed a landscape-scale, randomized-block design to identify how reptile assemblages initially responded to restoration treatments including removal of hardwood trees via mechanical methods (felling and girdling), application of herbicides, or prescribed burning alone. Then, we examined reptile assemblages after all sites experienced more than a decade of prescribed burning at 2- to 3- year return intervals. Data were collected concurrently at reference sites chosen to represent target conditions for restoration. Reptile assemblages changed most rapidly in response to prescribed burning but reptile assemblages at all sites, including reference sites, were generally indistinguishable by the end of the study. Thus, we suggest prescribed burning in longleaf pine forests over long time-periods is an effective strategy for restoring reptile assemblages to the reference condition. Application of herbicides or mechanical removal of hardwood trees provided no apparent benefit to reptiles beyond what was achieved by prescribed fire alone.

Mitchell, R. J., J. K. Hiers, L. K. Kirkman, A. Barnett, S. Zeigler, J. R. Walters, and S. M. Pokswinski. The Dynamic Reference Concept: Refining Components of Recovery in a Longleaf Pine Ecosystem. SERDP Partners in Environmental Technology Symposium, Washington DC, 2011.

Abstract: The objective of this study is to apply the Dynamic Reference Concept to the measurement of ecological recovery. As a model ecosystem, we use longleaf pine grasslands of the southeastern United States that provide habitat for the federally endangered red-cockaded woodpecker (RCW) and is known for its high levels of floral biodiversity. To understand recovery we first define reference conditions, then refine our understanding of reference condition through quantification of their spatial and temporal dynamics, and finally measure recovery of degraded sites towards these dynamic targets. To quantify this approach we (1) resampled six large (81-ha) plots that were intensively studied reference sandhills for a landscape restoration experiment from 1993-1998; (2) resampled 30 1-ha high quality reference conditions from the extensive monitoring program at Eglin AFB, and (3) resampled 20 81-ha oak removal plots from the original 1993-1998 study.

Pokswinski, S. M., L. K. Kirkman, J. K. Hiers, A. Barnett, and R. J. Mitchell. Building a Dynamic Reference Model: Developing Tools for Managing a Changing Ecosystem. Natural Areas Conference. Tallahassee, Florida, 2011.

Abstract: Development of reference models that can withstand the dynamism of ecosystems with increasing challenges from climate change and invasive species will become an important part of future conservation research. The objective of this study is to define a resilient reference model for managing sandhill ecosystems to aid in the recovery of the Red-cockaded woodpecker (RCW) on military bases. We resampled an experiment led by The Nature Conservancy from 1993-1998, and reference sandhill sites in an existing monitoring program at Eglin AFB. This sampling effort will be used to develop a dynamic reference model that gauges the impact of common forest restoration and management practices (herbicides, fire and timber harvests) and predict the direction and rate of recovery with respect to ecosystem management objectives. Our preliminary multivariate analyses of vegetation composition change shows that measurement of restoration success is further complicated by a reference condition that changes both spatially and temporally. Using Mahalanobis distance in NMDS space to measure restoration success over time, all treatments approached reference condition. However, reference plots also moved significantly over time. While providing insight into the impact of specific management practices, these results highlight the complexity of identifying elements of reference conditions that should be used to assess ecological recovery.

Kirkman, L. K., J. K. Hiers, A. Barnett, S. M. Pokswinski, and R. J. Mitchell. Quantifying Long Term Biodiversity Trends in a Spatially and Temporally Dynamic Ecosystem. Ecological Society of America Annual Meeting, Austin, Texas, 2011.

Abstract: Quantification of long term vegetation biodiversity trends in a species-rich, spatially and temporally dynamic ecosystem is a complex task because of the need to account for annual population fluctuations, disturbance cycles, as well as long term climatic changes. Monitoring restoration trajectories are further complicated by the fact that the reference condition, or desired restoration endpoint itself is changing over time. Vegetation monitoring of extremely diverse ecosystems, such as the fire-maintained longleaf pine ecosystem leads to "noisy" data that is problematic as a basis for management decisions. At Eglin AFB we are using a multi-method approach for quantifying dynamic reference conditions (desired future trajectory), measuring recovery rates of degraded sandhills in response to management, and building a Decision Support Framework to help managers meet restoration goals.

Kirkman, L. K., L. L. Smith, M. Conner, D. A. Steen, M. Mack, M. Lavoie, J. K. Hiers, A. Barnett, S. M. Pokswinski, J. R. Walters, and R. J. Mitchell. 2010. Restoration of a longleaf pine ecosystem: defining components of a dynamic reference model. SERDP Partners in Environmental Technology Symposium, Washington DC, 2010.

Abstract: Defining reference models for measuring ecological recovery continues to be a priority research need for ecological restoration. We couple the need for development of science-based recovery objectives for ecological systems in the southeastern United States with the recovery of the Red-cockaded woodpecker (RCW), which is a high conservation priority on several military bases. The premise of the dynamic ecological reference model is that habitat recovery must be considered in the context of continually changing reference

conditions. At Eglin AFB we are quantifying dynamic reference conditions (desired future trajectory), measuring recovery rates of degraded sandhills in response to management, and building a Decision Support Framework to help managers meet restoration goals.

B. Tables

Appendix B-1. List of problematic species lumped into morphospecies.

Morphospecies	**Species**
Andropogon spp.	*A. gerardii, A. ternarius*
Aristida spp.	*A. mohrii, A. purpurascens*
Bulbostylis spp.	*B. ciliatifolia, B. warei*
Cyperus retrorsus	*C. retrofractus, C. retrorsus*
Cliftonia monophylla	*C. monophylla, Cyrilla racemiflora*
Dichanthelium spp.	all *Dichanthelium* spp.
Houstonia procumbens	*Houstonia* spp., *H. procumbens*
Hypericum hypericoides	*H. crux-andreae, H. hypericoides*
Liatris spp.	all *Liatris* spp.
Physalis arenicola	*P. angustifolia, P. arenicola, P. longifolia*
Rhynchospora grayii	*R. grayii, R. megalocarpa*
Scleria ciliata	*S. ciliata, S. triglomerata*
Scutellaria incana	*S. glabriuscula, S. incana*
Sorghastrum secundum	*S. nutans, S. secundum*
Tragia spp.	*T. smallii, T. urens, T. urticifolia*
Vaccinium spp.	*V. corymbosum, V. myrsinites, V. stamineum*

Appendix B-2. List of plant species sampled, guild and disturbance class. Guild definitions include T=tree, S=shrub, GC=ground cover, E=evergreen, D=deciduous. In the disturbance column, longleaf=longleaf pine associate.

Species	Family	Guild	Disturbance
Acer rubrum	Sapindaceae	woody-T,D	semiruderal
Agalinis setacea	Scrophulariaceae	forb	semiruderal
Ageratina aromatica	Asteraceae	forb	longleaf
Andropogon glomeratus	Poaceae	graminoid	longleaf
Andropogon gyrans	Poaceae	graminoid	longleaf
Andropogon virginicus	Poaceae	graminoid	longleaf
Anthaenantia villosa	Poaceae	graminoid	longleaf
Aristida condensata	Poaceae	graminoid	semiruderal
Aristida lanosa	Poaceae	graminoid	longleaf
Aristida stricta	Poaceae	graminoid	longleaf
Aristolochia serpentaria	Aristolochiaceae	forb	longleaf
Asclepias cinerea	Asclepiadaceae	forb	longleaf
Asclepias humistrata	Asclepiadaceae	forb	longleaf
Asclepias tuberosa	Asclepiadaceae	forb	longleaf
Axonopus fissifolius	Poaceae	graminoid	ruderal
Balduina angustifolia	Asteraceae	forb	semiruderal
Balduina uniflora	Asteraceae	forb	longleaf
Baptisia calycosa	Fabaceae	forb	longleaf
Baptisia lanceolata	Fabaceae	forb	longleaf
Berlandiera pumila	Asteraceae	forb	longleaf
Bulbostylis ciliatifolia	Cyperaceae	graminoid	semiruderal
Calamintha dentata	Lamiaceae	forb	semiruderal
Callicarpa americana	Verbenaceae	woody-S,D	longleaf
Carex tenax	Cyperaceae	graminoid	longleaf
Castanea pumila	Fagaceae	woody-T,D	longleaf
Ceanothus microphyllus	Rhamnaceae	woody-GC,E	longleaf
Centrosema virginianum	Fabaceae	forb	longleaf
Chamaecrista fasciculata	Fabaceae	forb	semiruderal
Chamaecrista nictitans	Fabaceae	forb	semiruderal
Chrysoma pauciflosculosa	Asteraceae	forb	ruderal
Chrysopsis gossypina	Asteraceae	forb	longleaf
Clematis reticulata	Ranunculaceae	forb	longleaf
Cliftonia monophylla	Cyrillaceae	woody-T,E	mesic
Clitoria mariana	Fabaceae	forb	longleaf
Cnidoscolus stimulosus	Euphorbiaceae	forb	semiruderal
Commelina erecta	Commelinaceae	forb	semiruderal
Conyza canadensis	Asteraceae	forb	ruderal
Crataegus michauxii	Rosaceae	woody-S,D	semiruderal
Croptilon divaricatum	Asteraceae	forb	ruderal
Crotalaria purshii	Fabaceae	forb	longleaf
Crotalaria rotundifolia	Fabaceae	forb	longleaf
Croton argyranthemus	Euphorbiaceae	forb	semiruderal
Ctenium aromaticum	Poaceae	graminoid	longleaf

Cyperus croceus	Cyperaceae	graminoid	semiruderal
Cyperus filiculmis	Cyperaceae	graminoid	longleaf
Cyperus retrorsus	Cyperaceae	graminoid	longleaf
Dalea pinnata	Fabaceae	forb	longleaf
Danthonia sericea	Poaceae	graminoid	longleaf
Desmodium ciliare	Fabaceae	forb	longleaf
Desmodium laevigatum	Fabaceae	forb	longleaf
Desmodium lineatum	Fabaceae	forb	longleaf
Desmodium strictum	Fabaceae	forb	longleaf
Digitaria ciliaris	Poaceae	graminoid	ruderal
Digitaria cognata	Poaceae	graminoid	ruderal
Diodia teres	Rubiaceae	forb	ruderal
Diospyros virginiana	Ebenaceae	woody-T,D	semiruderal
Elephantopus elatus	Asteraceae	forb	semiruderal
Eragrostis spectabilis	Poaceae	graminoid	ruderal
Eragrostis virginica	Poaceae	graminoid	semiruderal
Erechtites hieracifolius	Asteraceae	forb	ruderal
Erigeron strigosus	Asteraceae	forb	ruderal
Eriogonum tomentosum	Polygonaceae	forb	longleaf
Eupatorium compositifolium	Asteraceae	forb	semiruderal
Euphorbia discoidalis	Euphorbiaceae	forb	longleaf
Euphorbia floridana	Euphorbiaceae	forb	semiruderal
Euthamia caroliniana	Asteraceae	forb	ruderal
Galactia erecta	Fabaceae	forb	longleaf
Galactia regularis	Fabaceae	forb	longleaf
Gaura filipes	Onagraceae	forb	semiruderal
Gaylussacia dumosa	Ericaceae	woody-GC,D	longleaf
Gaylussacia frondosa	Ericaceae	woody-GC,D	longleaf
Gaylussacia mosieri	Ericaceae	woody-GC,D	longleaf
Gymnopogon ambiguus	Poaceae	graminoid	longleaf
Gymnopogon brevifolius	Poaceae	graminoid	longleaf
Helianthemum carolinianum	Cistaceae	forb	longleaf
Helianthus radula	Asteraceae	forb	longleaf
Hieracium gronovii	Asteraceae	forb	longleaf
Houstonia procumbens	Rubiaceae	forb	longleaf
Hypericum gentianoides	Clusiaceae	woody-GC,D	ruderal
Hypericum hypericoides	Clusiaceae	woody-GC,E	semiruderal
Hypericum tetrapetalum	Clusiaceae	woody-GC,E	semiruderal
Hypoxis juncea	Liliaceae	forb	longleaf
Ilex ambigua	Aquifoliaceae	woody-S,D	longleaf
Ilex coriacea	Aquifoliaceae	woody-S,E	semiruderal
Ilex glabra	Aquifoliaceae	woody-S,E	semiruderal
Ilex opaca	Aquifoliaceae	woody-T,E	semiruderal
Ilex vomitoria	Aquifoliaceae	woody-S,E	seimruderal
Ionactis linarifolia	Asteraceae	forb	longleaf
Iris verna	Iridaceae	forb	longleaf
Juncus marginatus	Juncaceae	graminoid	longleaf
Kalmia hirsuta	Ericaceae	woody-GC,E	longleaf

Krameria lanceolata	Krameriaceae	forb	longleaf
Lechea sessiliflora	Cistaceae	forb	longleaf
Lespedeza capitata	Fabaceae	forb	longleaf
Lespedeza repens	Fabaceae	forb	longleaf
Licania michauxii	Chrysobalanaceae	woody-GC,E	longleaf
Lupinus diffusus	Fabaceae	forb	longleaf
Lyonia lucida	Ericaceae	woody-S,E	semiruderal
Magnolia virginiana	Magnoliaceae	woody-T,E	semiruderal
Mimosa quadrivalvis	Fabaceae	forb	longleaf
Minuartia caroliniana	Caryophyllaceae	forb	longleaf
Mitchella repens	Rubiaceae	forb	semiruderal
Myrica cerifera	Myricaceae	woody-S,E	semiruderal
Opuntia humifusa	Cactaceae	forb	semiruderal
Opuntia pusilla	Cactaceae	forb	semiruderal
Panicum verrucosum	Poaceae	graminoid	semiruderal
Panicum virgatum	Poaceae	graminoid	semiruderal
Paronychia patula	Caryophyllaceae	forb	ruderal
Physalis arenicola	Solanaceae	forb	semiruderal
Pinus clausa	Pinaceae	woody-T,E	ruderal
Pinus palustris	Pinaceae	woody-T,E	longleaf
Pityopsis aspera	Asteraceae	forb	semiruderal
Pityopsis graminifolia	Asteraceae	forb	semiruderal
Polygala polygama	Polygalaceae	forb	longleaf
Polygonella gracilis	Polygonaceae	forb	semiruderal
Polypremum procumbens	Buddleiaceae	forb	ruderal
Prunus serotina	Rosaceae	woody-T,D	semiruderal
Pseudognaphalium obtusifolium	Asteraceae	forb	ruderal
Pteridium aquilinum	Dennstaedtiaceae	forb	semiruderal
Pterocaulon pycnostachyum	Asteraceae	forb	semiruderal
Pycnanthemum pycnanthemoides	Lamiaceae	forb	ruderal
Quercus geminata	Fagaceae	woody-T,E	longleaf
Quercus incana	Fagaceae	woody-T,D	longleaf
Quercus laevis	Fagaceae	woody-T,D	longleaf
Quercus laurifolia	Fagaceae	woody-T,E	semiruderal
Quercus margaretta	Fagaceae	woody-T,D	longleaf
Quercus minima	Fagaceae	woody-GC,E	longleaf
Quercus myrtifolia	Fagaceae	woody-S,E	semiruderal
Rhexia alifanus	Melastomataceae	forb	longleaf
Rhexia mariana	Melastomataceae	forb	ruderal
Rhexia petiolata	Melastomataceae	forb	semiruderal
Rhus copallinum	Anacardiaceae	woody-S,D	seimruderal
Rhynchosia cytisoides	Fabaceae	forb	longleaf
Rhynchosia reniformis	Fabaceae	forb	longleaf
Rhynchospora grayi	Cyperaceae	graminoid	longleaf
Rhynchospora plumosa	Cyperaceae	graminoid	semiruderal
Rubus cuneifolius	Anacardiaceae	forb	ruderal
Ruellia caroliniensis	Acanthaceae	forb	longleaf
Salvia azurea	Lamiaceae	forb	longleaf

Schizachyrium sanguineum	Poaceae	graminoid	semiruderal
Schizachyrium scoparium	Poaceae	graminoid	longleaf
Schizachyrium tenerum	Poaceae	graminoid	semiruderal
Scleria ciliata	Cyperaceae	graminoid	longleaf
Scutellaria incana	Lamiaceae	forb	longleaf
Serenoa repens	Arecaceae	woody-S,E	semiruderal
Sericocarpus tortifolius	Asteraceae	forb	longleaf
Seymeria cassioides	Scrophulariaceae	forb	semiruderal
Silphium compositum	Asteraceae	forb	longleaf
Sisyrinchium nashii	Iridaceae	forb	semiruderal
Smilax auriculata	Smilacaceae	forb	semiruderal
Smilax bona-nox	Smilacaceae	forb	semiruderal
Smilax glauca	Smilacaceae	forb	semiruderal
Solidago odora	Asteraceae	forb	longleaf
Sorghastrum secundum	Poaceae	graminoid	longleaf
Sporobolus junceus	Poaceae	graminoid	longleaf
Stillingia sylvatica	Euphorbiaceae	forb	longleaf
Stipulicida setacea	Caryophyllaceae	forb	longleaf
Stylisma patens	Convolvulaceae	forb	semiruderal
Stylosanthes biflora	Fabaceae	forb	longleaf
Symphyotrichum adnatum	Asteraceae	forb	longleaf
Symphyotrichum concolor	Asteraceae	forb	longleaf
Symphyotrichum dumosum	Asteraceae	forb	longleaf
Tephrosia chrysophylla	Fabaceae	forb	longleaf
Tephrosia florida	Fabaceae	forb	longleaf
Tephrosia hispidula	Fabaceae	forb	longleaf
Tephrosia spicata	Fabaceae	forb	longleaf
Tephrosia virginiana	Fabaceae	forb	longleaf
Tradescantia hirsutiflora	Commelinaceae	forb	semiruderal
Trichostema setaceum	Lamiaceae	forb	ruderal
Triplasis americana	Poaceae	graminoid	seimruderal
Vaccinium arboreum	Ericaceae	woody-S,E	semiruderal
Vaccinium darrowii	Ericaceae	woody-GC,E	longleaf
Vernonia angustifolia	Asteraceae	forb	longleaf
Viola palmata	Violaceae	forb	longleaf
Vitis rotundifolia	Vitaceae	forb	ruderal
Xyris caroliniana	Xyridaceae	forb	longleaf
Yucca filamentosa	Agavaceae	forb	semiruderal

Appendix B-3. Results of the FDR correction multiple comparisons procedure. For each treatment, “Y” or “n” indicates whether or not distance was significant.

Soil characteristics	**Reference**	**Burn**	**Control**	**Herbicide**	**Mechanical**
Bulk Density (g cm^{-3})	n	n	Y	n	n
Moisture Content (%)	n	n	n	n	n
C (%)	n	Y	Y	Y	Y
N (%)	n	Y	Y	Y	Y
C:N ratio	n	n	n	n	n
C (g m^{-2})	n	n	Y	Y	n
N (g m^{-2})	n	n	n	n	n
NH_4 (g N gdw^{-1})	n	n	n	n	n
NO_3 (g N gdw^{-1})	n	n	n	n	n
NH_4 (g m^{-2})	n	n	n	n	n
NO_3 (g m^{-2})	n	n	n	n	n
Ammonification (g N $gdw^{-1}d^{-1}$)	n	n	n	n	n
Nitrification (g N $gdw^{-1}d^{-1}$)	n	n	Y	n	n
Mineralization (g N $gdw^{-1}d^{-1}$)	n	n	n	n	n
Ammonification (g N $m^{-2}d^{-1}$)	n	n	n	n	n
Nitrification (g N $m^{-2}d^{-1}$)	n	n	Y	n	n
Mineralization (g N $m^{-2}d^{-1}$)	n	n	n	n	n
Initial C flux rate (µg C gdw^{-1} h^{-1})	n	n	n	n	n
6-week C flux rate (µg C gdw^{-1} h^{-1})	n	n	n	n	n
Plant functional group					
Grasses	n	n	n	n	n
Forbs	n	n	n	n	n
Woody	Y	Y	n	n	n
Saw palmetto	n	n	n	n	n

Appendix B-4. Comparison of group size and demographic rates[1] for RCW populations observed between 2000 and 2010 in (*i*) the Sandhills of North Carolina (basis for the Sandhills type locality in the RCW Population Model), (*ii*) MCBCL (basis for the Coastal type locality) and (*iii*) Eglin AFB.

Demographic Rate	Sandhills Population	MCBCL Population	Eglin AFB Population
Average group size (# adults per group per year)	2.59	2.84	2.52
Survival – Males (%)			
Fledgling	47.94	52.04	47.93
Breeder	78.07	83.14	79.69
Helper	77.91	82.56	70.80
Solitary	77.86	73.91	83.33
Floater	59.89	74.19	63.64
Survival – Females (%)			
Fledgling	33.28	43.64	37.42
Breeder	71.33	77.47	75.00
Helper	58.73	64.84	63.27
Floater	64.71	70.63	44.74
Stage Transitions – Males (%)			
Fledgling - Breeder	4.22	3.69	1.78
Fledgling - Helper	37.33	43.50	40.24
Fledgling - Solitary	1.60	1.36	2.37
Fledgling - Floater	4.74	3.50	3.55
Breeder - Breeder	76.76	82.57	79.31
Breeder - Helper	0.12	0.00	0.38
Breeder - Solitary	0.86	0.43	0.00
Breeder - Floater	0.33	0.14	0.00
Helper - Breeder	20.97	18.74	24.82
Helper - Helper	54.70	62.34	45.99
Helper - Solitary	1.12	0.19	0.00
Helper - Floater	1.06	1.30	0.00
Solitary - Breeder	54.96	56.52	66.67
Solitary - Helper	0.00	0.00	16.67
Solitary - Solitary	21.37	17.39	0.00
Solitary - Floater	1.53	0.00	0.00
Floater - Breeder	40.11	38.71	18.18
Floater - Helper	4.95	3.23	18.18
Floater - Solitary	4.40	12.90	9.09
Floater - Floater	10.44	19.35	18.18
Stage Transitions – Females (%)			
Fledgling - Breeder	22.17	16.13	9.82
Fledgling - Helper	4.67	11.39	17.18
Fledgling - Floater	6.28	16.13	10.43
Breeder - Breeder	70.25	75.61	72.95
Breeder - Helper	0.12	0.14	0.00
Breeder - Floater	0.79	1.72	2.05
Helper - Breeder	34.92	34.07	31.25

Helper - Helper	21.43	27.47	31.25
Helper - Floater	2.38	3.30	0.00
Floater - Breeder	47.55	49.21	26.32
Floater - Helper	5.39	5.56	15.79
Floater - Floater	11.76	15.87	2.63
Breeding			
Average percentage of females	75%	75%	75%
Average number of offspring per clutch	2.17	2.03	1.74
Total % of clutches producing 1 fledgling	22.05%	24.10%	38.61%
Total % of clutches producing 2 fledglings	43.10%	51.29%	48.51%
Total % of clutches producing 3 fledglings	30.39%	22.38%	12.87%
Total % of clutches producing 4 fledglings	4.42%	2.24%	0%
Total % of clutches producing 5 fledglings	0.05%	0%	0%

[1]Note: demographic rates shown here have not been corrected for immigration into and emigration out of the study areas. The impact of these rates on survival is expected to be particularly high for Eglin AFB, where the "population" from which survival and reproduction is calculated is actually a subset of the full Eglin RCW population. The number of birds exchanged between the monitored territory subset and surrounding territories within Eglin is likely high.

Appendix B-5. Results of one-way PerMANOVA analysis to assess differences in ground cover vegetation between hardwood removal treatments and reference plots from 1994 to 2010[1].

Year	Effect	DF	SS	Mean Square	F-value	p-value*	Pairwise Comparisons	Pairwise p-value
1994	Treatment	4	0.31	0.08	1.69	0.0040	B-R	0.0120
	Residual	20	0.92	0.05			C-R	0.0100
	Total	24	1.23				M-R	0.0360
							H-R	0.0070
1995	Treatment	4	0.27	0.07	1.46	0.0170	B-R	0.0090
	Residual	20	0.93	0.05			C-R	0.0090
	Total	24	1.20				M-R	0.0170
							H-R	0.0070
1996	Treatment	4	0.29	0.07	1.50	0.0130	B-R	0.0140
	Residual	20	0.98	0.04			C-R	0.0110
	Total	24	1.27				M-R	0.0080
							H-R	0.0090
1997	Treatment	4	0.33	0.08	1.95	0.0010	B-R	0.0120
	Residual	20	0.85	0.04			C-R	0.0100
	Total	24	1.17				M-R	0.0370
							H-R	0.0070
							B-H[1]	0.0090
1998	Treatment	4	0.32	0.08	1.95	0.0010	B-R	0.0100
	Residual	20	0.81	0.04			C-R	0.0110
	Total	24	1.13				M-R	0.0210
							H-R	0.0190
							C-M[1]	0.0320
2010	Treatment	4	0.29	0.07	2.00	0.0010	B-R	0.0030
	Residual	20	0.71	0.04			C-R	0.0070
	Total	24	1.00				M-R	0.0060
							H-R	0.0080
							C-H[1]	0.0110

* proportion of randomized trials with indicator value equal to or exceeding the observed indicator value. p = (1 + number of runs >= observed)/(1 + number of randomized runs)
RCBD Results

[1]The differences between treatments were not significant at p < .05 when blocks were included in the RCBD analysis.

Appendix B-6. Results of RCBD PerMANOVA analysis to assess differences in ground cover vegetation among hardwood removal treatment plots from 1994 to 2010.

Year	**Effect**	**DF**	**SS**	**Mean Square**	**F-value**	**p-value***	**Pairwise Comparisons**
1994	Block	4	0.33	0.08	2.73	0.0010	None
	Treatment	3	0.11	0.04	1.18	0.2038	
	Residual	12	0.37	0.03			
	Total	19	0.81				
1995	Block	4	0.32	0.08	2.21	0.0010	None
	Treatment	3	0.12	0.04	1.15	0.2597	
	Residual	12	0.43	0.04			
	Total	19	0.87				
1996	Block	4	0.32	0.08	2.05	0.0010	None
	Treatment	3	0.12	0.04	1.03	0.4106	
	Residual	12	0.46	0.04			
	Total	19	0.90				
1997	Block	4	0.27	0.07	2.19	0.0010	None
	Treatment	3	0.18	0.06	1.91	0.0010	
	Residual	12	0.37	0.03			
	Total	19	0.82				
1998	Block	4	0.29	0.07	2.53	0.0010	None
	Treatment	3	0.16	0.05	1.93	0.0020	
	Residual	12	0.34	0.03			
	Total	19	0.79				
2010	Block	4	0.25	0.06	2.45	0.0010	None
	Treatment	3	0.13	0.04	1.73	0.0010	
	Residual	12	0.31	0.03			
	Total	19	0.70				

* proportion of randomized trials with indicator value equal to or exceeding the observed indicator value. p = (1 + number of runs >= observed)/(1 + number of randomized runs)

Appendix B-7. RCBD ANCOVA using 1994 PS to reference values as the covariate and PS to reference as response variable for each sampling year.

Year	**Effect**	**DF**	**Type III SS**	**Mean Square**	**F-value**	**p-value**	**Tukey Pairwise Comparisons**	**Pairwise p-value**
1994	Treatment	3	0.01	0.00	0.81	0.4899	None	
	Block	4	0.07	0.02	6.79	<0.0001		
1995	Treatment	3	0.03	0.01	4.56	0.0051	B-H	0.0023
	Block	4	0.03	0.01	3.54	0.0099		
	PS 94	1	0.11	0.11	46.16	<0.0001		
1996	Treatment	3	0.02	0.01	4.60	0.0048	B-C	0.0304
	Block	4	0.02	0.01	3.02	0.0217	B-H	0.0044
	PS 94	1	0.10	0.10	59.40	<0.0001		
1997	Treatment	3	0.01	0.00	2.48	0.0664	None	
	Block	4	0.01	0.00	1.78	0.1398		
	PS 94	1	0.08	0.08	49.44	<0.0001		
1998	Treatment	3	0.02	0.01	4.00	0.0101	B-C	0.0091
	Block	4	0.01	0.00	1.49	0.2129	B-H	0.0495
	PS 94	1	0.08	0.08	49.69	<0.0001		
2010	Treatment	3	0.01	0.00	1.68	0.1773	None	
	Block	4	0.00	0.00	0.59	0.6688		
	PS 94	1	0.04	0.04	28.77	<0.0001		

Appendix B-8. Results of the RCBD ANCOVA for ground cover species richness at the treatment scale by year. Pre-treatment species richness was used as the covariate for all years

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	130.00	43.33	0.41	0.7474	None	
	Block	4	145.00	112.50	1.07	0.4135		
1995	Treatment	3	142.52	47.51	3.25	0.0638	None	
	Block	4	58.08	14.52	0.99	0.4511		
	SR 94	1	1255.21	1255.21	85.87	<0.0001		
1996	Treatment	3	174.17	58.06	3.15	0.0687	B-H	0.0487
	Block	4	20.47	5.12	0.28	0.8864		
	SR 94	1	881.95	881.95	47.85	<0.0001		
1997	Treatment	3	316.12	105.37	3.06	0.0734		
	Block	4	31.92	7.98	0.23	0.9147	None	
	SR 94	1	682.69	682.69	19.83	0.0010		
1998	Treatment	3	279.41	93.14	5.15	0.0182	B-C	0.0438
	Block	4	27.67	6.92	0.38	0.8167	M-C	0.0274
	SR 94	1	710.48	710.48	39.29	<0.0001		
2010	Treatment	3	79.33	26.44	1.64	0.2368		
	Block	4	566.18	141.55	8.78	0.0020	None	
	SR 94	1	257.63	257.63	15.98	0.0021		

Appendix B-9. Tables of results of the RCBD ANCOVA for ground cover species richness at the plot scale by year. Pre-treatment species richness was used as the covariate for all years

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	78.22	26.07	0.53	0.6654	None	
	Block	4	1010.52	252.63	5.10	0.0012		
1995	Treatment	3	368.17	122.72	9.80	<0.0001	B-H	0.0019
	Block	4	115.83	28.96	2.31	0.0663	C-H	<0.0001
	SR 94	1	2676.64	2676.64	213.83	<0.0001	M-H	0.0003
1996	Treatment	3	406.69	135.56	11.64	<0.0001	B-H	<0.0001
	Block	4	75.79	18.95	1.63	0.1776	C-H	0.0004
	SR 94	1	2293.73	2293.73	196.91	<0.0001	M-H	0.0005
1997	Treatment	3	400.88	133.63	7.73	0.0002	B-H	<0.0001
	Block	4	81.54	20.38	1.18	0.3278	M-H	0.0218
	SR 94	1	2151.15	2151.15	124.44	<0.0001		
1998	Treatment	3	506.08	168.69	9.98	<0.0001	B-C	0.0047
	Block	4	29.81	7.45	0.44	0.7787	C-M	<0.0001
	SR 94	1	1467.86	1467.86	86.80	<0.0001	M-H	0.0021
2010	Treatment	3	191.83	63.94	1.92	0.1350	None	
	Block	4	369.17	92.29	2.77	0.0341		
	SR 94	1	246.66	246.66	7.40	0.0083		

Table B-10. Results of the RCBD analysis for ground cover species richness at the subplot scale by year. Pre-treatment species richness was used as the covariate for all years.

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	99.84	33.28	1.59	0.1923	None	
	Block	4	1604.03	401.01	19.13	<0.0001		
1995	Treatment	3	644.37	214.79	22.78	<0.0001	B-H	<0.0001
	Block	4	58.32	14.58	1.55	0.1887	C-H	<0.0001
	SR 94	1	4701.27	4701.27	498.65	<0.0001	M-H	<0.0001
1996	Treatment	3	861.99	287.33	35.48	<0.0001	B-H	<0.0001
	Block	4	19.45	4.86	0.60	0.6625	C-H	<0.0001
	SR 94	1	3993.19	3993.19	493.14	<0.0001	M-H	<0.0001
1997	Treatment	3	680.89	226.96	22.32	<0.0001	B-H	<0.0001
	Block	4	98.30	24.58	2.42	0.0488	C-H	<0.0028
	SR 94	1	3401.54	3401.54	334.57	<0.0001	M-H	<0.0001
1998	Treatment	3	579.85	193.28	19.18	<0.0001	B-H	0.0007
	Block	4	16.33	4.08	0.41	0.8050	C-M	<0.0001
	SR 94	1	2620.66	2620.66	259.99	<0.0001	M-H	<0.0001
							B-C	<0.0001
2010	Treatment	3	353.67	117.89	5.79	0.0007	B-H	0.0322
	Block	4	78.08	19.52	0.96	0.4303	C-M	0.0192
	SR 94	1	314.72	314.72	15.46	0.0001	C-H	0.0021

Table B-11. Results of the RCBD ANCOVA for ground cover species richness at the quadrat scale by year. Pre-treatment species richness (SR 94) was used as the covariate for all years.

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	60.98	20.33	2.02	0.1095	None	
	Block	4	1452.20	363.05	36.06	<0.0001		
1995	Treatment	3	433.94	144.65	32.63	<0.0001	B-H	<0.0001
	Block	4	39.73	9.93	2.24	0.0627	C-H	<0.0001
	SR 94	1	5995.22	5995.22	1352.46	<0.0001	M-H	<0.0001
1996	Treatment	3	687.11	229.04	47.91	<0.0001	B-H	<0.0001
	Block	4	24.13	6.033	1.26	0.2830	C-H	<0.0001
	SR 94	1	5832.93	5832.93	1220.10	<0.0001	M-H	<0.0001
1997	Treatment	3	679.63	226.54	35.16	<0.0001	B-C	<0.0001
	Block	4	63.95	15.99	2.48	0.0423	B-H	<0.0001
	SR 94	1	5501.70	5501.70	853.83	<0.0001	C-H	<0.0001
							M-H	<0.0001
1998	Treatment	3	400.26	133.42	21.28	<0.0001	B-C	<0.0001
	Block	4	123.84	30.96	4.94	0.0006	B-H	0.0004
	SR 94	1	4818.24	4818.24	768.46	<0.0001	C-M	<0.0001
							M-H	<0.0001
2010	Treatment	3	672.78	224.26	21.23	<0.0001	B-M	0.0179
	Block	4	159.43	39.86	3.77	0.0047	B-H	<0.0001
	SR 94	1	1131.40	1131.40	107.09	<0.0001	C-M	0.0007
							C-H	<0.0001
							M-H	0.0132

Appendix B-12._ Results of the RCBD ANCOVA for ground cover evenness at the treatment scale by year. Pre-treatment evenness (E 94) was used as the covariate for all years.

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	0.06	0.02	3.51	0.0494	None	
	Block	4	0.03	0.01	1.53	0.2548		
1995	Treatment	3	0.00	0.00	0.12	0.9477		
	Block	4	0.01	0.00	1.17	0.3762	None	
	E 94	1	0.06	0.06	21.30	0.0007		
1996	Treatment	3	0.00	0.00	0.59	0.6318		
	Block	4	0.01	0.00	3.84	0.0343	None	
	E 94	1	0.03	0.03	46.54	<0.0001		
1997	Treatment	3	0.00	0.00	1.25	0.3375		
	Block	4	0.00	0.00	0.03	0.9980	None	
	E 94	1	0.01	0.01	12.44	0.0047		
1998	Treatment	3	0.01	0.00	2.94	0.0806		
	Block	4	0.00	0.00	0.67	0.6280	None	
	E 94	1	0.01	0.01	7.78	0.0176		
2010	Treatment	3	0.00	0.00	0.78	0.5299		
	Block	4	0.02	0.00	4.02	0.0301	None	
	E 94	1	0.01	0.01	9.18	0.0115		

Appendix B-13. Results of the RCBD ANCOVA for ground cover average log abundance at the treatment scale by year. Pre-treatment average log abundance was used as the covariate for all years.

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	0.02	0.01	0.64	0.6011	None	
	Block	4	0.31	0.08	9.72	0.0010		
1995	Treatment	3	0.02	0.01	1.64	0.2378		
	Block	4	0.01	0.00	0.38	0.8207	None	
	A 94	1	0.04	0.04	9.34	0.0109		
1996	Treatment	3	0.04	0.01	4.36	0.0297		
	Block	4	0.03	0.01	2.44	0.1091	B-H	0.0410
	A 94	1	0.04	0.04	14.26	0.0031	C-H	0.0400
1997	Treatment	3	0.00	0.00	0.13	0.9410		
	Block	4	0.05	0.01	7.48	0.0037	None	
	A 94	1	0.02	0.02	14.22	0.0031		
1998	Treatment	3	0.01	0.00	2.27	0.1375		
	Block	4	0.03	0.01	6.03	0.0081	None	
	A 94	1	0.09	0.09	75.55	<0.0001		
2010	Treatment	3	0.02	0.01	2.55	0.1090		
	Block	4	0.13	0.03	10.04	0.0011	None	
	A 94	1	0.00	0.00	0.01	0.9121		

Appendix B-14. Results of the RCBD ANCOVA for ground cover abundance at the treatment scale by year and plant guild (forbs, graminoids, legumes, shrubs, and trees). 1994 density was used as the covariate.

Forbs

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	163640875233	54546958411	4.73	0.0211	M-V	0.0127
	Block	4	48771053943	121927634860	10.58	0.0007		
1995	Treatment	3	6290620774	209687359	0.95	0.4484		
	Block	4	14102828553	3525707138	1.60	0.2418	None	
	Forbs 94	1	36469821681	36469821681	16.59	0.0018		
1996	Treatment	3	15552134529	518404484	1.73	0.2176		
	Block	4	7871956699	1967989175	0.66	0.6333	None	
	Forbs 94	1	47913461663	47913461663	16.03	0.0021		
1997	Treatment	3	6534910621	2178303540	0.75	0.5440		
	Block	4	9500432320	2375108080	0.82	0.5390	None	
	Forbs 94	1	8372296858	8372296858	2.89	0.1173		
1998	Treatment	3	671840447	223946816	0.12	0.9452		
	Block	4	12408197903	3102049476	1.69	0.2220	None	
	Forbs 94	1	13328161685	1332816168	7.26	0.0209		
2010	Treatment	3	45885248514	15295082838	0.43	0.7363		
	Block	4	33845142498	33461285625	0.94	0.4772	None	
	Forbs 94	1	735298856739	735298856739	20.63	0.0008		

Graminoids

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	670445256	223481752	0.45	0.7245	None	
	Block	4	5502515071	1375628768	2.75	0.0783		
1995	Treatment	3	1015860181	338620060	3.83	0.0423	C-V	0.0327
	Block	4	329155541	82288885	0.93	0.4812		
	Gram 94	1	5676798786	5676798786	64.20	<0.0001		
1996	Treatment	3	2199402287	733134096	3.24	0.0481	B-V	0.0481
	Block	4	668806824	167201706	0.74	0.5848		
	Gram 94	1	6367009708	6367009708	28.13	0.0003		
1997	Treatment	3	1344493099	448164366	1.67	0.2300	None	
	Block	4	88976803	222244201	0.83	0.5337		

	Gram 94	1	5056904285	056904285	18.87	0.0012		
1998	Treatment	3	3252038055	1084012685	3.48	0.0539	C-V	0.0445
	Block	4	1329539181	332384795	1.07	0.4177		
	Gram 94	1	959732736	2959732736	9.51	0.0104		
2010	Treatment	3	65298829032	1766276344	3.26	0.0632		
	Block	4	60720893719	15180223430	2.27	0.1268	None	
	Gram 94	1	35582399	35582399	0.01	0.9431		

Legumes

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons
1994	Treatment	3	483439117	161146372	0.67	0.5882	None
	Block	4	1158508320	289627080	1.20	0.3609	
1995	Treatment	3	380412658	126804219	1.86	0.1950	
	Block	4	817462093	204365523	3.00	0.0672	None
	Legume 94	1	3343134402	343134402	49.00	<0.0001	
1996	Treatment	3	490202202	163400734	1.57	0.2515	None
	Block	4	1176591972	294147993	2.83	0.0772	
	Legume 94	1	2900137359	2900137359	27.92	0.0003	
1997	Treatment	3	37053121	12351040	0.74	0.5525	
	Block	4	289187254	72296814	4.30	0.0245	None
	Legume 94	1	1761198722	761198722	104.85	<0.0001	
1998	Treatment	3	47400343	15800114	0.33	0.8019	
	Block	4	1018526479	254631620	5.36	0.0121	None
	Legume 94	1	1340634003	1340634003	28.24	0.0002	
2010	Treatment	3	5631598196	1877199399	2.51	0.1132	
	Block	4	29320267277	330066819	9.78	0.0013	None
	Legume 94	1	3596183427	3596183427	4.80	0.0509	

Shrubs

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons
1994	Treatment	3	58984778	19661593	2.50	0.1087	None
	Block	4	74433591	18608398	2.37	0.1108	

1995	Treatment	3	4190008	1396669	1.01	0.4239	
	Block	4	954966	238741	0.17	0.9476	None
	PS 94	1	92612272	92612272	67.14	<0.0001	
1996	Treatment	3	8242146	2747382	0.81	0.5158	
	Block	4	3089910	772478	0.23	0.9176	None
	PS 94	1	190931458	190931458	56.10	<0.0001	
1997	Treatment	3	1509373	3836458	0.76	0.5419	
	Block	4	12657777	3164444	0.62	0.6556	None
	PS 94	1	86700105	86700105	17.07	0.0017	
1998	Treatment	3	6684506	2228169	0.55	0.6569	
	Block	4	6161321	1540330	0.38	0.8170	None
	PS 94	1	58166177	8166177	14.43	0.0030	
2010	Treatment	3	279502494	93167498	1.64	0.2368	
	Block	4	33173649	58293412	1.03	0.4361	None
	PS 94	1	182498598	82498598	3.21	0.1006	

Trees

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	230997587	76999196	0.98	0.4343	None	
	Block	4	502663284	125665821	1.60	0.2375		
1995	Treatment	3	604057172	201352391	10.92	0.0013	B-C	0.0395
	Block	4	87858513	21964628	1.19	0.3678	B-V	0.0008
	Tree 94	1	548204584	548204584	29.73	0.0002	M-V	0.0282
1996	Treatment	3	1324710388	441570129	12.11	0.0008	B-V	0.0010
	Block	4	73459245	18364811	0.50	0.7342	C-V	0.0155
	Tree 94	1	1151129072	1151129072	31.56	0.0002	M-V	0.0031
1997	Treatment	3	886530570	2962176857	4.50	0.0271	B-V	0.0260
	Block	4	212029234	803007309	1.22	0.3570		
	Tree 94	1	936191238	936191238	1.42	0.2581		
1998	Treatment	3	2483683492	827894497	4.82	0.0222	B-V	0.0135
	Block	4	791732535	197933134	1.15	0.3825		
	Tree 94	1	453552138	453552138	2.64	0.1323		
2010	Treatment	3	1669382986	556460995	3.00	0.0771		
	Block	4	2465627750	616406937	3.32	0.0516	None	
	Tree 94	1	629747733	629747733	3.39	0.0927		

Appendix B-15. Midstory abundance at the treatment scale. ANCOVA with 1994 values as covariate.

Quercus geminata

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons
1994	Treatment	3	7124	2375	0.34	0.7969	None
	Block	4	44644	11161	1.60	0.2381	
1997	Treatment	3	38812	12937	2.59	0.1059	None
	Block	4	15323	3831	0.77	0.5689	
	QUEGEM 94	1	29089	29089	5.82	0.0345	
1998	Treatment	3	46449	15483	2.19	0.1461	None
	Block	4	22541	5635	0.80	0.5504	
	QUEGEM 94	1	28866	28866	4.09	0.0681	
2010	Treatment	3	3886	1295	1.20	0.3547	None
	Block	4	5715	1428	1.32	0.3207	
	QUEGEM 94	1	2947	2947	2.73	0.1265	

Deciduous Oaks

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons	Pairwise p-value
1994	Treatment	3	1455295	485098	1.24	0.3395	None	
	Block	4	1612481	403120	1.03	0.4323		
1997	Treatment	3	2263433	754478	3.78	0.0439	None	
	Block	4	817544	204386	1.02	0.4376		
	DECOAK 94	1	1201443	1201443	6.01	0.0321		
1998	Treatment	3	2278291	759430	3.47	0.0544	None	
	Block	4	1205325	301331	1.38	0.3042		
	DECOAK 94	1	1349311	1349311	6.16	0.0304		
2010	Treatment	3	614033	204678	6.28	0.0097	H-M	0.0061
	Block	4	509080	127270	3.90	0.0328		
	DECOAK 94	1	134466	134466	4.12	0.0672		

Appendix B-16. Results of the RCBD ANCOVA (1994 density) for number of ruderal species in the ground cover at the treatment scale by year. Analysis only included ruderal species (i.e., semi-ruderal species were not included)

Year	Effect	DF	Type III SS	Mean Square	F-value	p-value	Tukey Pairwise Comparisons
1994	Treatment	3	3589817	1196606	0.59	0.6308	None
	Block	4	10052624	2513156	1.25	0.3429	
1995	Treatment	3	672307	224102	0.85	0.4941	None
	Block	4	1069754	267439	1.02	0.4402	
	Tree 94	1	20022090	20022090	76.14	<0.0001	
1996	Treatment	3	88968715	29656239	0.47	0.7119	None
	Block	4	159005893	39751473	0.62	0.6547	
	Tree 94	1	14781684	14781684	0.23	0.6393	
1997	Treatment	3	119932160	39977387	0.82	0.5115	None
	Block	4	138269198	34567299	0.71	0.6045	
	Tree 94	1	1759076	1759076	0.04	0.8532	
1998	Treatment	3	766848080	255616027	4.32	0.0305	None
	Block	4	205027303	51256826	0.87	0.5140	
	Tree 94	1	6783379	6783379	0.11	0.7413	
2010	Treatment	3	6216304028	2072101343	3.54	0.0516	None
	Block	4	4792872930	1198218233	2.05	0.1566	
	Tree 94	1	381966102	381966102	0.65	0.4361	

Appendix B-17. Indicator species and change in frequency (F) and abundance (A) for reference (REF) conditions and treatment (TRT) sites.

Species	**1994**	**2010**	**Prior monitoring Eglin indicators**	**Change in (A) or (F) 1994-2010 REF**	**Change in (A) or (F) 1994-2010 TRT**
*Ageratina aromatica**	X	X		A-, F-	A+, F+
Andropogon gyrans		X		A-, F-	A-, F-
Andropogon spp.	X			A-, F	A+, F
Aristida stricta	X		X	A+, F-	A+, F+
Bulbostylis ciliatifolia	X			A+, F	A+, F+
Crotalaria rotundifolia		X	X	A+, F+	A+, F-
Cyperus filiculmis		X		A+, F+	A+, F+
Digitaria cognata	X			A-, F+	A+, F+
Eupatorium compositifolium	X			A-, F	A+, F+
Euphorbia discoidalis	X			A+, F-	A+, F+
*Gymnopogon ambiguus**		X		A+, F+	A+, F+
Helianthemum carolinianum	X	X		A+, F+	A+, F+
Houstonia procumbens	X			A-, F-	A+, F+
Hypericum gentianoides	X			A-, F-	A+, F+
Hypericum hypericoides		X		A+, F+	A+, F-
Hypoxis juncea					
*Ionactis linariifolia**		X		A+, F	A+, F+
Lechea sessiliflora	X	X		A+, F	A+, F+
*Lespedeza repens**		X		A+, F+	A+, F-
Pinus palustris	X			A-, F	A+, F+
Pityopsis graminifolia		X	X	A-, F	A+, F
Pseudognaphalium obtusifolium	X			A-, F-	A+, F+
Rhus copallinum	X			A+, F	A+, F+
Solidago odora	X		X	A+, F	A+, F+
*Stylisma patens**		X		A+, F	A+, F
Symphyotrichum concolor	X	X		A+, F	A+, F+
Symphyotrichum dumosum		X		A+, F+	A+, F+
*Tephrosia florida**	X	X		A+, F	A+, F+
Tephrosia spicata		X		A, F	A+, F+
Vaccinium darrowii		X		A+, F+	A+, F
*Viola palmata**	X	X		A+, F	A+, F+
Yucca filamentosa	X			A+, F-	A+, F+

* Indicates that species is primarily associated with wettest reference site based on analyses omitting this reference plot.
A- = net abundance decreased from 1994 to 2010 (sum of all abundances for each species, broken out by treatment vs. reference

A+ = net abundance increased from 1994 to 2010 (sum of all abundances for each species, broken out by treatment vs. reference
A = no net change in abundance
F- = frequency (# of plots in which the spp was found) decreased from 1994 to 2010 (sum of all abundances for each species, broken out by treatment vs. reference
F+ = frequency increased from 1994 to 2010 (sum of all abundances for each species, broken out by treatment vs. reference
F = no change in frequency

C. Figures

Appendix C-1. Figures showing mean ±1 SE of ground cover species richness at the plot (Fig. A), sub-plot (Fig. B), and quadrat (Fig. C) scales for treatment and reference plots from 1994 to 2010. Means with different letters are significantly different (Tukey's HSD, $p < 0.05$). Reference plots were not included in the ANCOVA and are shown only for visual comparison.

Figure A

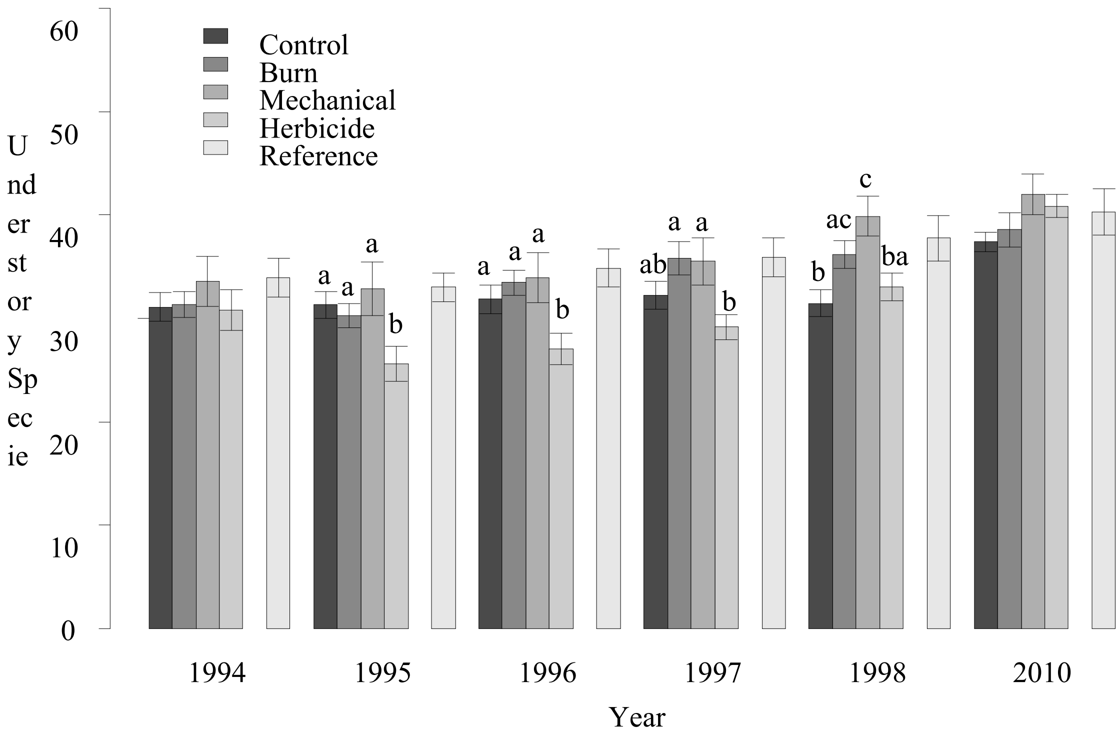

Figure B

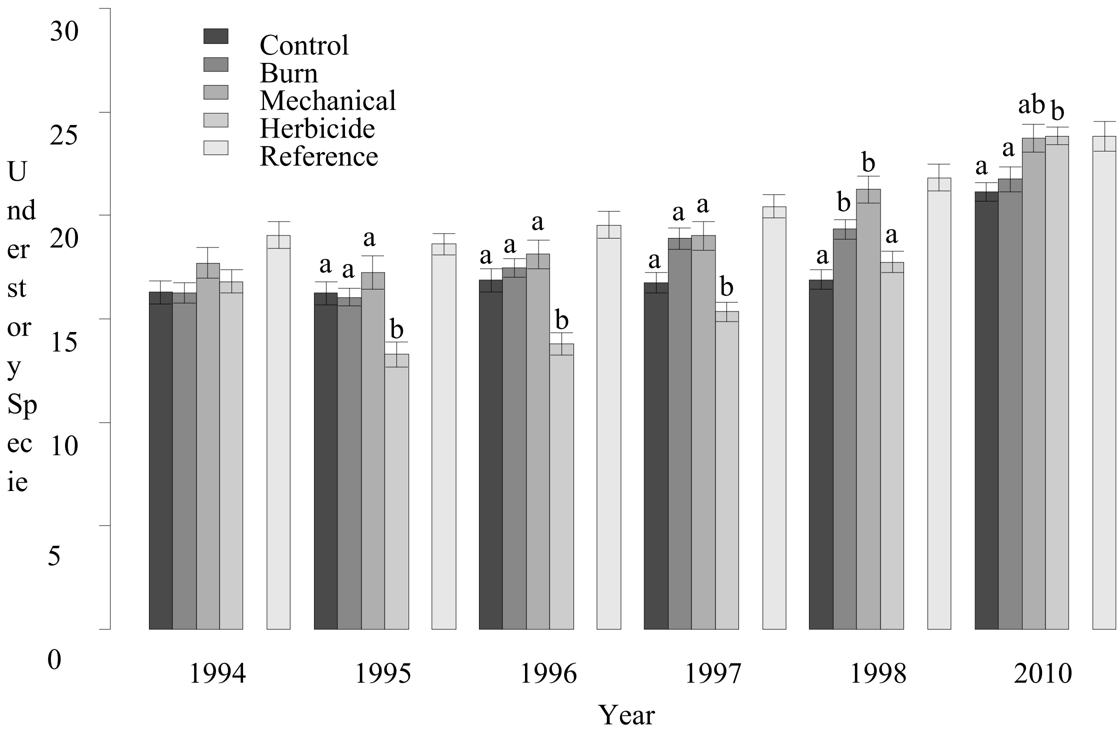

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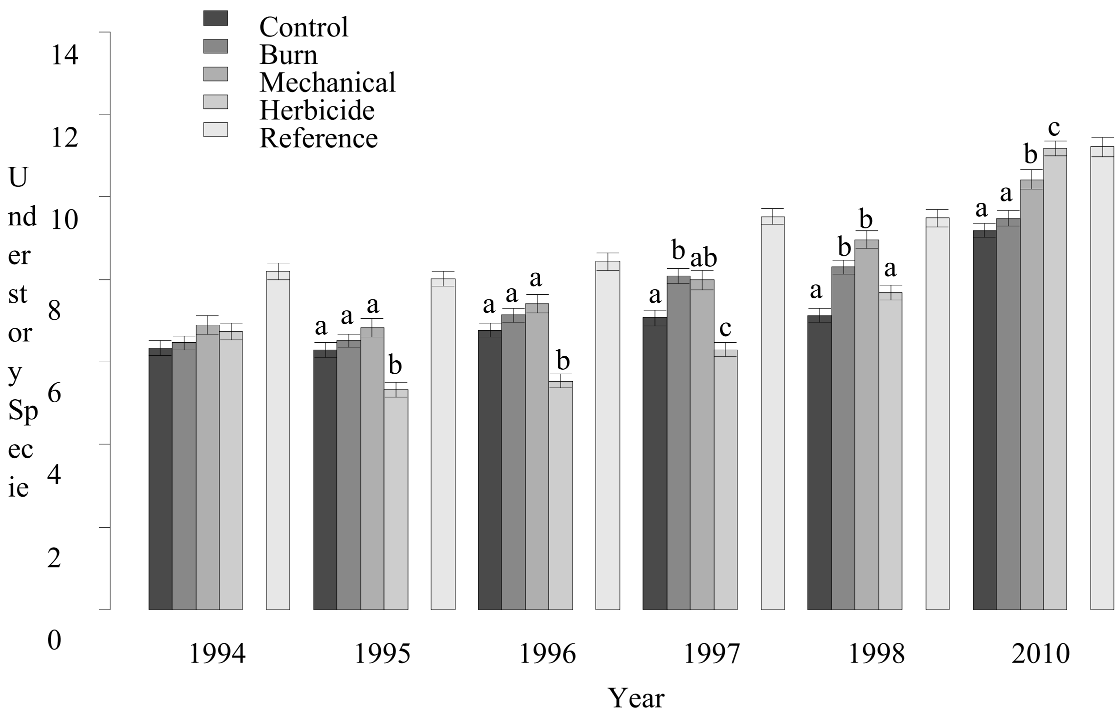
Figure C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D. User's Guide for Eglin AFB State-and-Transition Model

Author: Sara Zeigler
Parameterization: Sara Zeigler and Jeffrey Walters (Virginia Tech), Robert Mitchell (Jones Ecological Research Center), J. Kevin Hiers (Eglin AFB), and Analie Roberts (TNC).
Model: Parameterization and screenshots specific to ST-SIM (ApexRMS) version 2.1.0
Date: November 2014

1. Introduction

We developed a model of successional-disturbance dynamics in a longleaf pine ecosystem in order to simulate RCW population-level responses to landcover change. Outputs from the landscape model, which include both spatially explicit and non-spatially explicit descriptions of the landcover types that comprise a given area, can be used as inputs into an RCW-specific population model (Walters et al. 2011; Figure D-1.1). Our landscape model was constructed within the existing program ST-SIM (Daniel & Frid 2011), which is a state-and-transition model that simulates future landcover conditions by considering interactions between successional processes, unplanned disturbances, and planned changes to the landscape. In this manual, we focus on the parameterization of the ST-SIM landscape model that is specific to Eglin AFB (Figure D-1.2). However, this model will also been modified for use at MCBCLand Fort Bragg, and these models will be described at a later date in this manual.

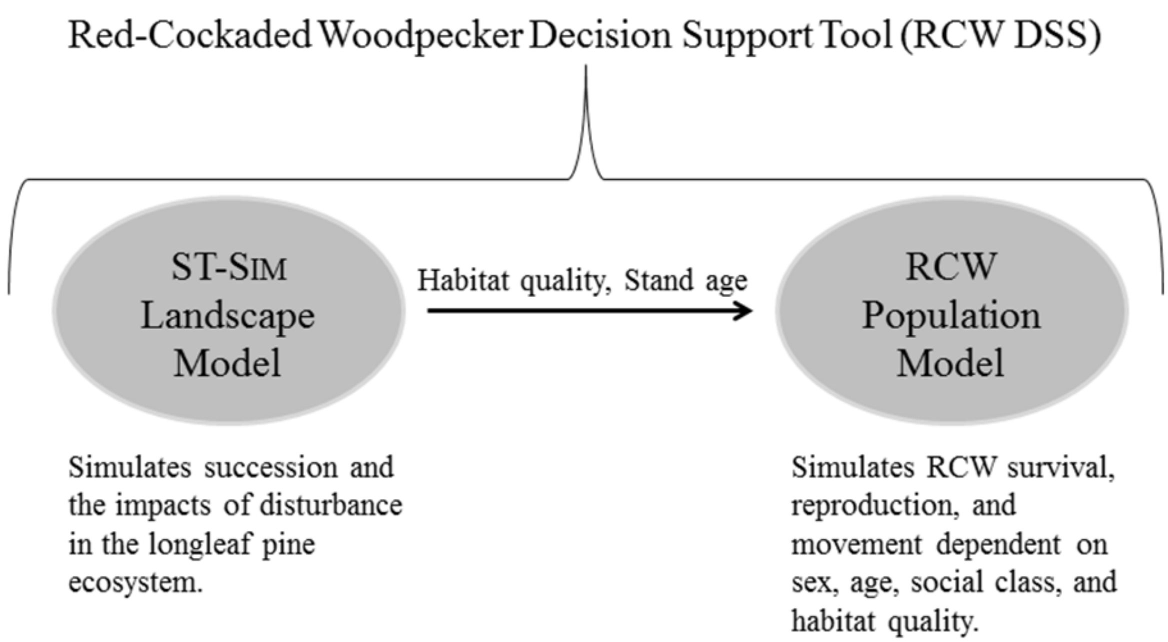


Figure D-1.1 Conceptualization of the linked ST-SIM landscape – RCW population model, an applied tool for RCW conservation.

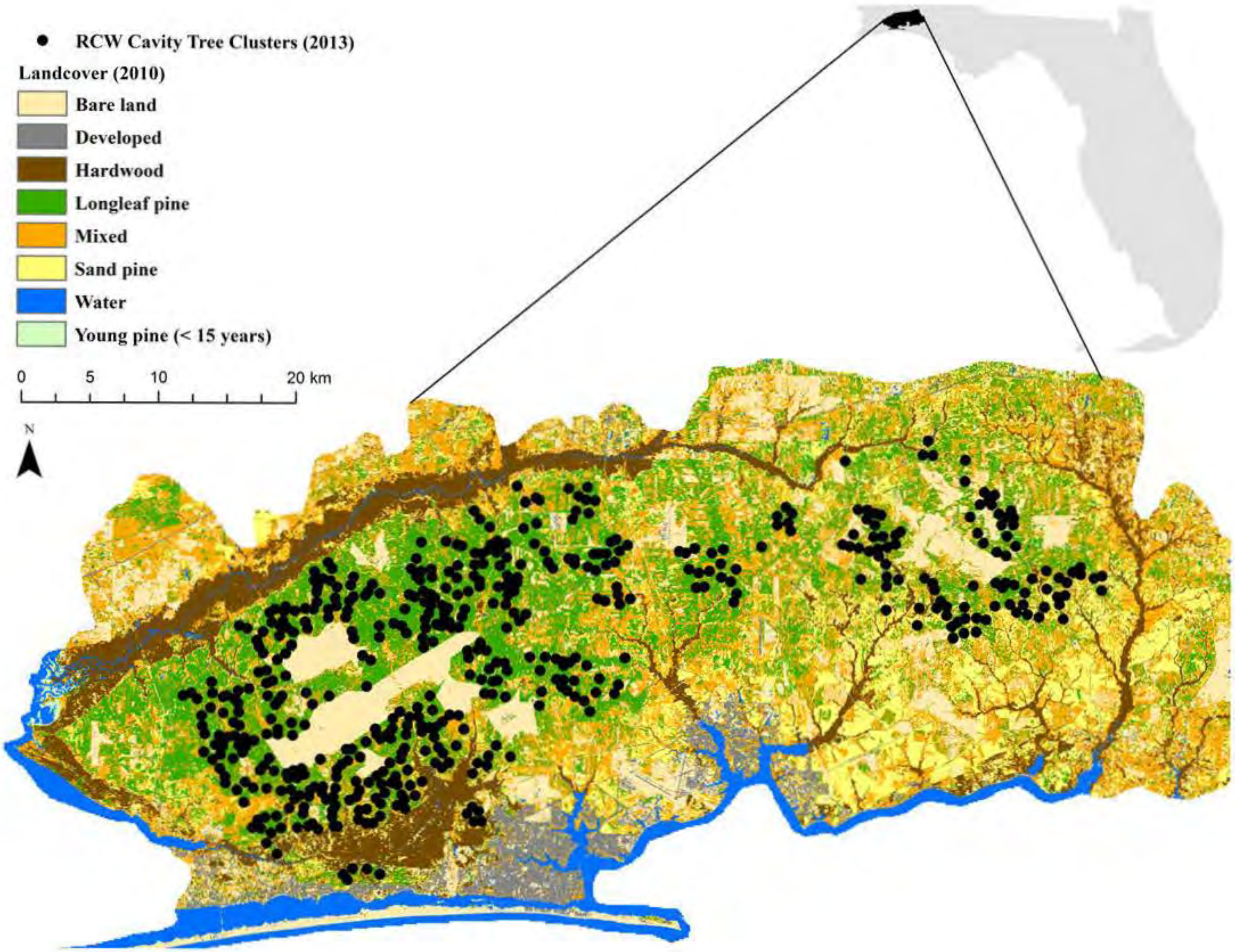


Figure D-1.2 RCW territories (year 2013) and the underlying landcover classes at Eglin AFB (year 2010).

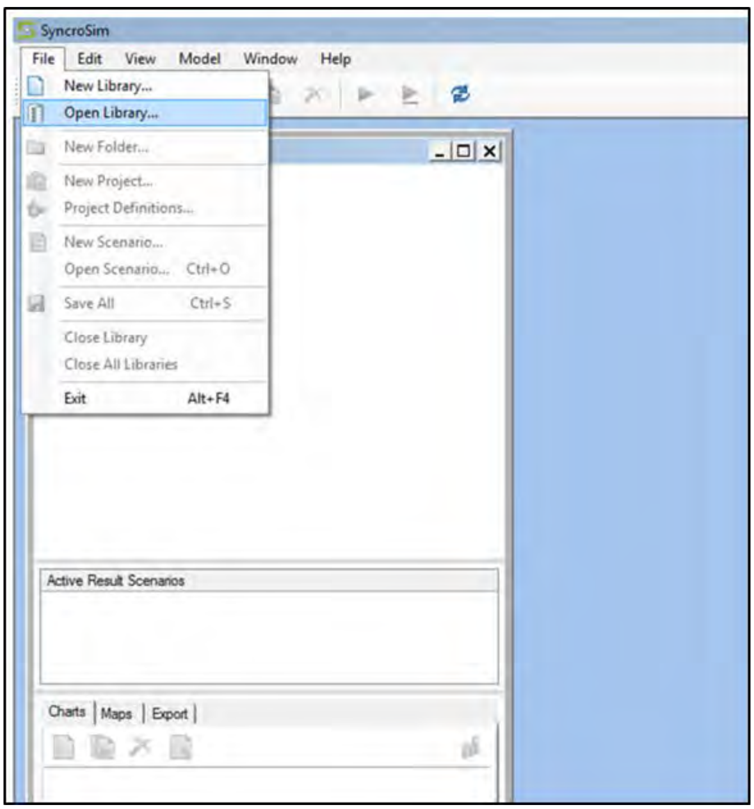
2. Downloading ST-SIM

ST-SIM is a freely available state-and-transition modeling platform available from ApexRMS at http://www.apexrms.com. Download the zip file for the most recent version of the software (current version at time this guide was written: 2.3.8). Unzip the file's contents to the location of your choice, and run the setup application to install the software. The installation file is also available in the zip file "RCW_STSim" that accompanies this manual.

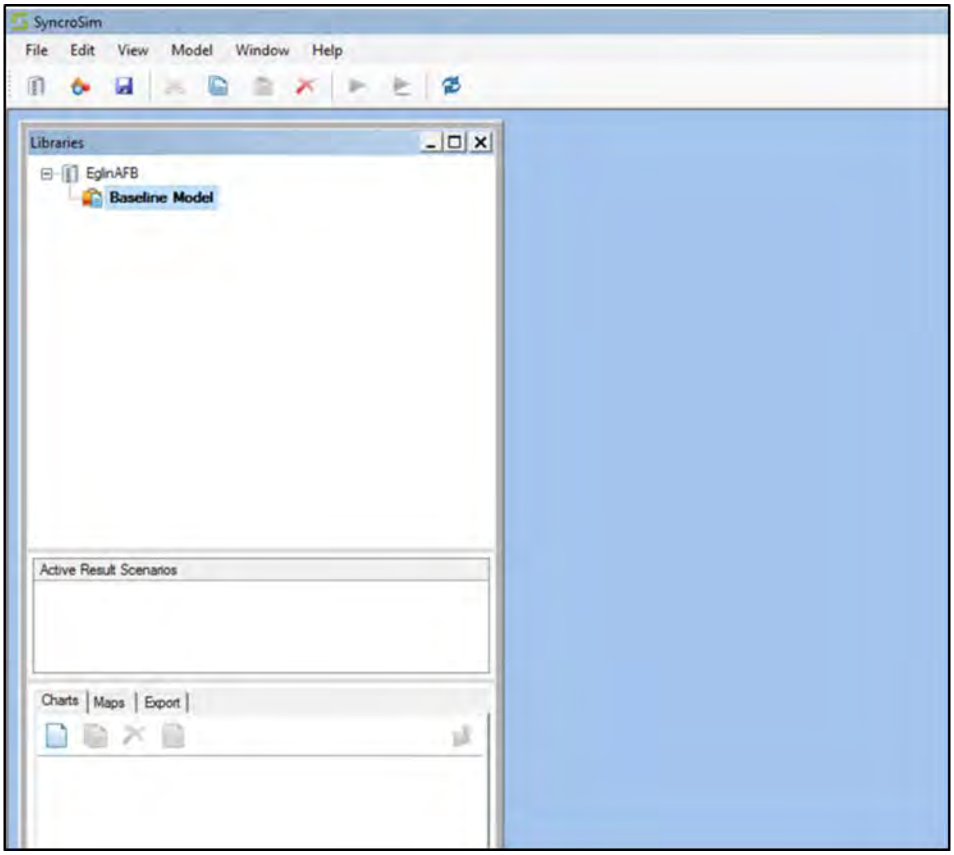
3. ST-SIM Quick Run

As the user, you can choose to construct the Eglin state and transition model from scratch from the steps outlined in *Section 4. Parameterizing the Model* of this user's manual. This section also details how to adjust certain parameters to test potential landcover changes and management approaches in longleaf pine ecosystems.

However, to immediately run the ST-SIM model, you can open the ST-SIM library that accompanies this user manual. Unzip the file "RCW_STSim", and extract the files and folders within this zip file. Then, open the ST-SIM program (which may appear on your computer as "SyncroSim"). Click on "File" along the top menu bar in the main ST-SIM window, and select "Open Library".

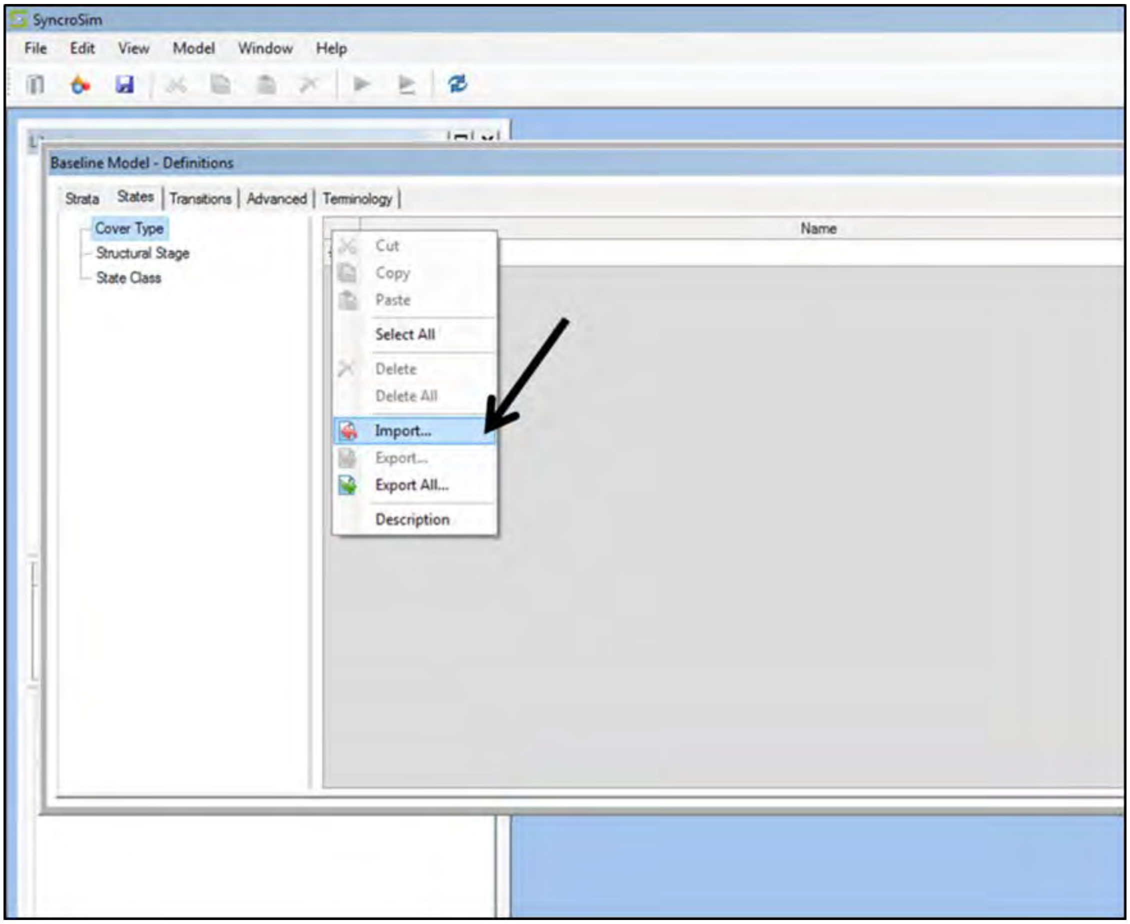


In the "Open Library" window that appears, navigate to the unzipped folder that accompanied this manual, and select the ST-SIM file "EglinAFB.ssim". The model, which was specifically parameterized for the longleaf pine ecosystem at Eglin AFB, will then appear in the "Libraries" menu.



You can then set the initial conditions (*Section 4.5 Simulation Controls and Initial Conditions*), run the model (*Section 5. Running the ST-SIM Model*), and evaluate the results (*Section 6. ST-SIM Results and Outputs*).

In addition, many of the input windows described throughout *Section 4. Parameterizing the Model* contain tables. These tables can be exported, manipulated in Microsoft Excel, and then imported back into the ST-SIM model. For example, right click on the "Basic Transitions" scenario in the "Libraries" window. In the "Baseline Model – Definitions" window that appears, click on the "States" tab, and then click on "Cover Type" to the left of this tab. In the table within this window, right click on the cell in the top-left corner of this table. From the drop-down list that appears, you can select "Export" to export all entries from this table to an Excel file, or you can select "Import" to import an Excel file that will parameterize this table.



In the zip file that accompanies this manual, we included a series of Excel parameter files in the subfolder "Quick Start Files – Baseline" that were exported from tables throughout the ST-SIM model. These Excel files and their associated locations throughout the model are given in Table D-1.1.

Table D-1.1 Locations associated with Excel parameter files included with this manual.

Excel File Name	**Associated Location in the ST-SIM model**
EglinAFB_Baseline_Strata	Project Definitions – Strata – Vegetation Type
EglinAFB_Baseline_CoverType	Project Definitions[1] – States – Cover Type
EglinAFB_Baseline_StructuralStage	Project Definitions[1] – States – Structural Stage
EglinAFB_Baseline_StateClass	Project Definitions[1] – States – State Class
EglinAFB_Baseline_TransitionGroup	Project Definitions[1] – Transitions – Transition Group
EglinAFB_Baseline_TransitionType	Project Definitions[1] – Transitions – Transition Type
EglinAFB_Baseline_TransitionTypeGroup	Project Definitions[1] – Transitions – Transition Types by Group
EglinAFB_Baseline_DeterministicTransitions	Basic Transitions[2] – Pathways – Deterministic Transitions (lower tab)
EglinAFB_Baseline_ProbabilisticTransitions	Basic Transitions[2] – Pathways – Probabilistic Transitions (lower tab)
EglinAFB_Baseline_TransitionTargets	Basic Transitions[2] – Advanced – Transitions Targets
EglinAFB_Baseline_Fire_Distribution	Basic Transitions[2] – Advanced – Transitions Spatial – Size Distribution
EglinAFB_Initial_Conditions_2010	Basic Transitions[2] – Initial Conditions – Non-Spatial

[1]This window is accessed by right-clicking on the scenario name in the "Libraries" window in the main ST-SIM screen.
[2]This window is accessed by double-clicking on the scenario name in the "Libraries" window in the main ST-SIM screen.

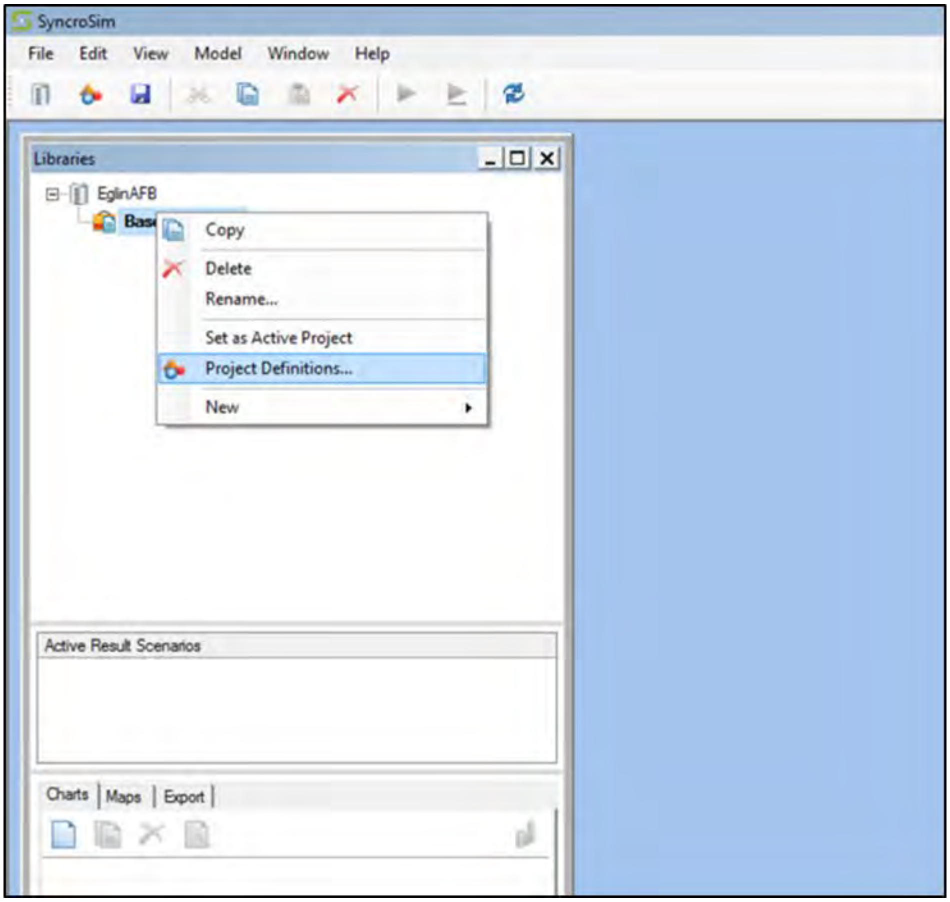
4. Parameterizing the Model

In this section, we describe how the user can build and ST-SIM landscape model from scratch. Throughout this section, we specifically describe the steps taken to construct the baseline model of longleaf pine ecosystem dynamics for Eglin AFB. After downloading and opening ST-SIM, go to "File" and "New Library" to create a new project library. You will be prompted to name and save this library at the location of your choice (currently saved as "EglinAFB"). Next, right-click on the library's name, and select "New" and "Project". You will again be prompted to name and save this project at the location of your choice (currently saved as "Baseline Model"). From there, you will be able to specifically parameterize the ST-SIM model to simulate the dynamics of the longleaf pine ecosystem.

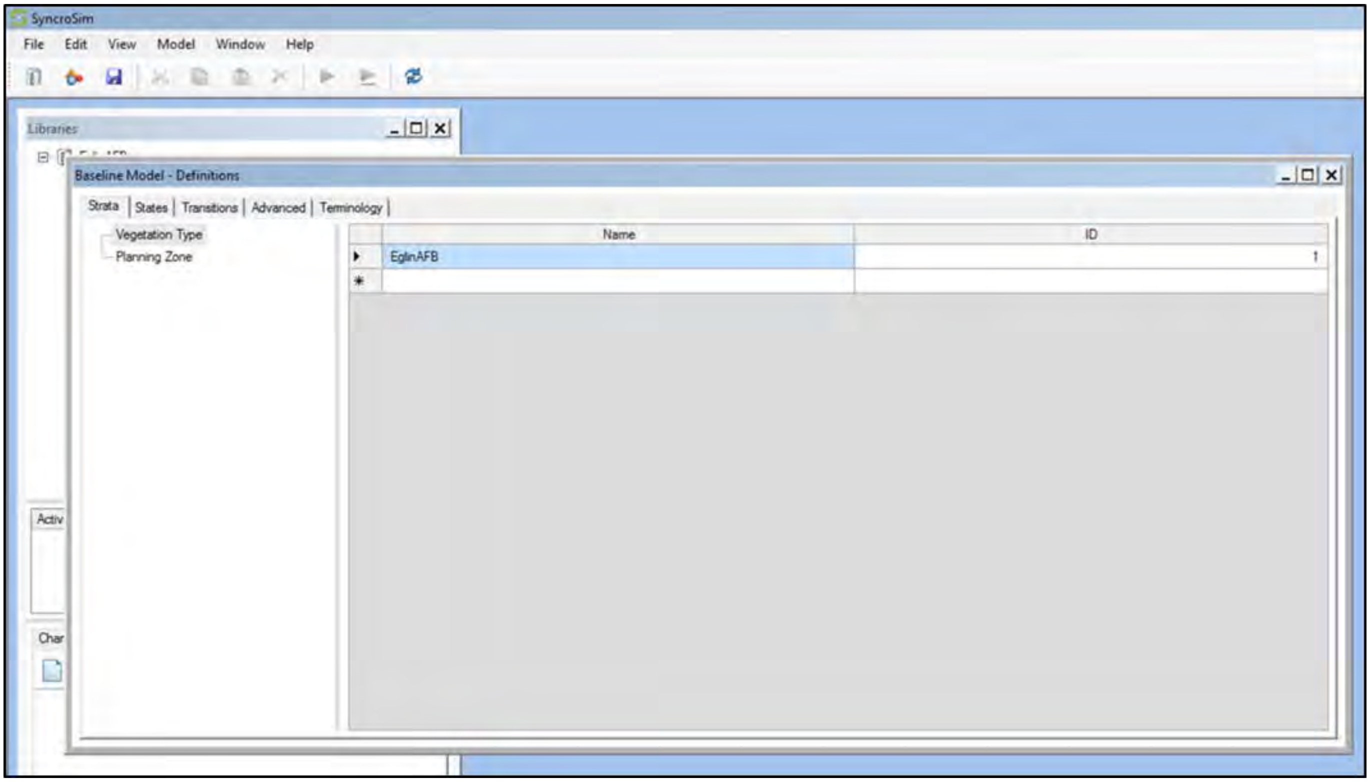
Data and published literature used to select parameters for our model are described in more detail in the report that accompanies this user's manual.

4.1 Landscape States

The basic units of any ST-SIM model are the landscape strata, states, and transitions that govern changes between specific landscape classes. This information is added through the "Project Definitions" window that is accessed by right-clicking on the project name in the "Libraries" window and selecting "Project Definitions".



In the first tab ("Strata"), the types of strata represented in the model can be added. These are the major underlying classifications of the landscape, such as ecoregions or soil types, that govern the type of vegetation that can grow in specific areas. In this model of Eglin AFB, the underlying classification is the same for the entire base, so only one strata type will be added (Name: "EglinAFB"; ID: 1). ID values given in this window and in all others represent the identification value associated with this strata type (or landcover state) on maps used in spatially explicit simulations.



Next, specify the landscape states, which are the basic units of any ST-SIM model and are discrete classes representing specific landcover types, successional states, or other landscape characteristics (e.g., tree density, species composition, etc). These states are generally further categorized by a "Cover Type" and a "Structural Class". In developing this ST-SIM model, it was necessary to create states that were relevant both to the longleaf pine ecosystem and to RCW biology/ecology while also being compatible within the RCW population model. Thus, we included states for Longleaf Pine, Young Pine (i.e., stands in which the oldest cohort of trees is less than 15 years of age), Mixed (i.e., mixed pine and hardwood stands), Hardwood, Developed, Sand Pine, Bare Land, and Water. The Longleaf Pine class was further broken down into two sets of multi-state successional pathways, where each state represents a specific range in stand age, canopy BA, midstory suitability, and percentage cover of herbaceous plants in the understory (Table D-1.2, Figure D-1.3).

Table D-1.2 Thresholds for categories describing canopy BA, midstory density and height, and understory cover used in the ST-SIM landscape model of longleaf pine ecosystem dynamics.

Category	Threshold Value	References and Support
Canopy BA (i.e. trees $\geq$ 25 cm DBH)		
High BA Moderate / Suitable BA Low BA	> 15.75 m^2/ha (70 ft^2/ac) 2.25 – 15.75 m^2/ha (10 – 70 ft^2/ac) < 2.25 m^2/ha (10 ft^2/ac)	Average BA for stands preferred by RCWs was 16.1 m^2/ha (70 ft^2/ac ; Porter & Labisky 1986). 2003 recovery criteria require a BA of at least 9.2 m^2/ha for trees $\geq$25 cm DBH (40 ft^2/ac; USFWS 2003). Stands avoided by RCWs had BAs 17.0 m^2/ha (74 ft^2/ac; Porter & Labisky 1986). Stand densities reported north of Florida range from 9.2 – 13.8 m^2/ha (40 – 60 ft^2/ac; reviewed in Hopkins & Lynn 1971; USFWS 2003). Median BA for stands with RCWs in FL panhandle was 10.6 m^2/ha (46 ft^2/ac; Hovis & Labisky 1985).
Midstory Suitability		
High Suitability Moderate Suitability Low Suitability	BA < 100 m^2/ha Height $\leq$ 2 m and BA 100 – 200 m^2/ha Height > 2 m and BA > 200 m^2/ha	Median midstory height for stands with RCWs in FL panhandle was 1.6 m (Hovis & Labisky 1985). 2003 recovery criteria require that midstory height be less than 2.1 m (USFWS 2003). Loeb et al. (1992) found a significant difference between the midstory BA of stands with active RCW clusters (average BA = 135 m^2/ha) and those with inactive clusters (average BA = 244 m^2/ha).
Understory Cover (i.e., % cover by native grasses and other herbs)		
High Percent Cover Low Percent Cover	$\geq$ 40% < 40%	James et al. (2001) found that health of RCW populations was related to groundcover composition and recommend that wiregrass or other herbaceous groundcover constitutes at least 40% of the total groundcover. Also listed as a requirement in recovery criteria (USFWS 2003).

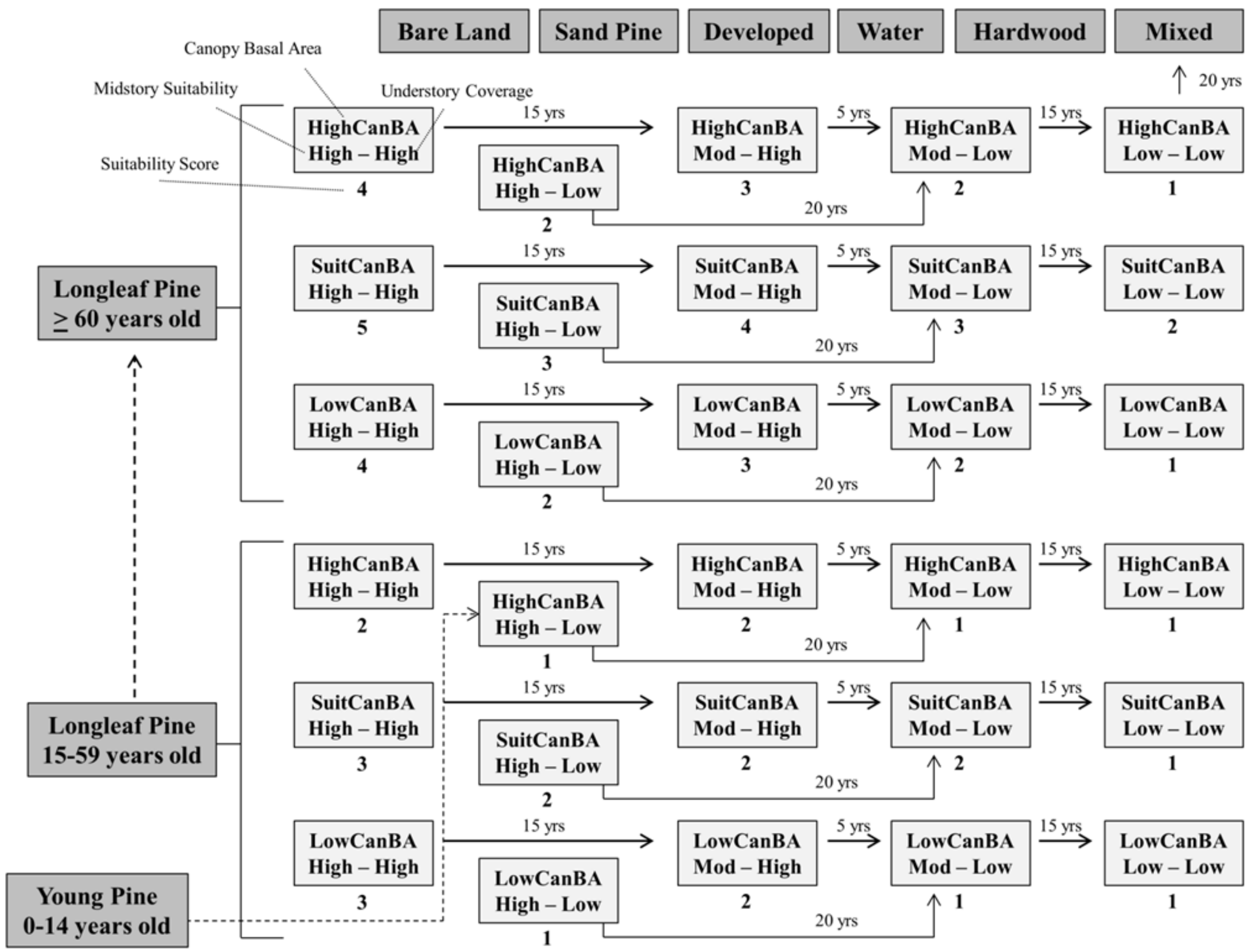


Figure D-1.3 Landcover states in the ST-SIM landscape model and their connections through succession (solid arrows) and aging (dashed arrows). Stands can also age from any state in the Longleaf Pine 15-59 years class to the equivalent state within the Longleaf Pine ≥ 60 years class if stand age progresses past those age thresholds during a simulation (arrows not shown). In this model, succession from one state to the next occurs if a disturbance (e.g., fire) has not occurred in that stand in 5 to 20 year increments. Each state is associated with a RCW habitat suitability score (number under state box; all non-longleaf pine states have the lowest possible suitability value of 1). See Table D-1.2 for quantitative thresholds associated with qualitative states shown here.

Longleaf Pine States

Preferred habitat for RCWs consists of mature, open longleaf pine savannas with large trees, sparse or no midstory, and lush herbaceous ground cover (Hardesty et al. 1997; James et al. 2001; USFWS 2003; Walters et al. 2002). In the longleaf pine ecosystem, fire, or lack thereof, imposes major changes to forest structure and composition such that habitat is most suitable for RCWs at higher fire return intervals, and suitability declines over longer periods of fire suppression. This trend is reflected in the ST-SIM model through the inclusion of four longleaf pine classes for each canopy BA class, where midstory suitability and herbaceous understory

coverage decline with increasing time since the last fire (Table D-1.2; Figure D-1.3). In these states, midstory suitability is described by a combination of height and density. A midstory with high suitability has a BA < 100 m^2/ha; a midstory with moderate suitability has a BA between 100 – 200 m^2/ha and a height $\leq$ 2 m; and a midstory with low suitability has a BA > 200 m^2/ha and a height > 2 m. Similarly, because RCW fitness and stand-use decline with decreasing understory coverage by native herbs (Hardesty et al. 1997; James et al. 2001; James et al. 1997), we described the understory as having either High Coverage of herbaceous plants ($\geq$ 40% of total groundcover) or Low Coverage (< 40% of total ground cover; Table D-1.2; Figure D-1.3).

Although fire and fire suppression have major impacts on the understory and midstory, they have little impact on canopy BA, with the exception of very intense canopy-scorching burns that occur after prolonged periods of fire suppression (Varner et al. 2005). Accordingly, canopy BA will not change appreciably following most disturbances on the landscape or over relatively short periods of successional growth in the absence of disturbance (Brockway & Lewis 1997; Myers 1990). At the same time, RCWs preferentially forage in longleaf pine stands or patches within those stands that have lower (but not open) canopy BAs (Bowman et al. 1997; Doster & James 1998; Walters et al. 2000; Walters et al. 2002). To capture this difference in habitat preference/suitability, we included three levels of canopy BA in the ST-SIM model (Table D-1.2; Figure D-1.3): High BA Canopy (> 15.75 m^2/ha), Suitable BA Canopy (2.25-15.75 m^2/ha), and Low BA Canopy (< 2.25 m^2/ha). For each level of canopy BA, the hardwood midstory suitability and understory characteristics for a given stand vary as described in the previous paragraph (Figure 18).

Finally, multiple studies have found that RCWs select large old trees over small young trees for foraging (Bradshaw 1995; DeLotelle et al. 1987; Engstrom & Sanders 1997; Hardesty et al. 1997; Hooper & Lennartz 1981; Jones & Hunt 1996; Porter & Labisky 1986; Walters et al. 2000; Walters et al. 2002; Zwicker & Walters 1999). In the ST-SIM model, we tracked stand ages and created two separate sets of Longleaf Pine classes to capture stands in which the oldest cohort was $\geq$ 60 years of age vs. stands in which the oldest cohort was between 15 and 59 years of age (Figure D-1.3). Stands in which the oldest cohort was < 15 years of age were categorized as the Young Pine state. Using multiple age-based groupings allowed us to differentiate habitat suitability according to stand age and the successional dynamics in the midstory and understory while enabling stands to naturally progress from being completely unsuitable (< 15 years) to marginally suitable ($\geq$ 15 years) to highly suitable ($\geq$ 60 years) for foraging. Because tree age consistently correlates with RCW habitat suitability and other habitat characteristics throughout the species range, the basic premises of the landscape model are transferable to other sites.

Other Landcover States

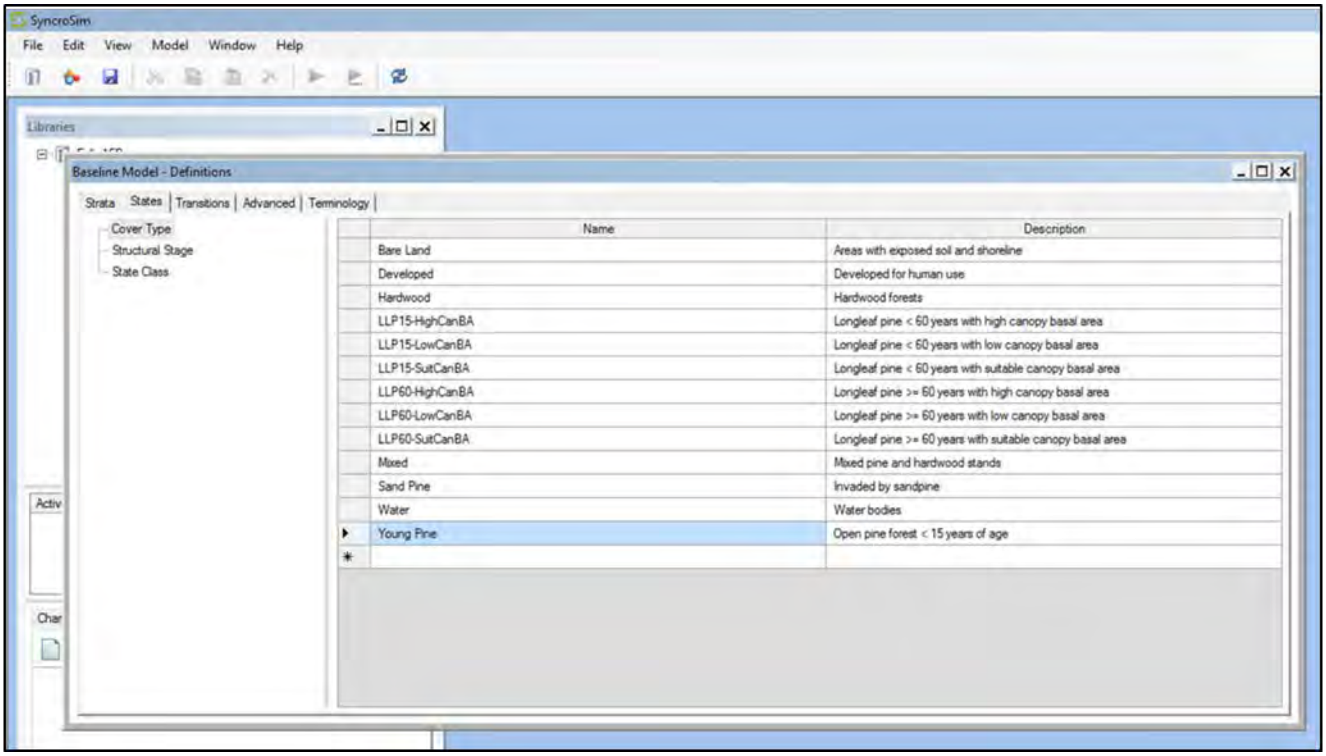
We also included landcover states for Hardwood, Mixed, Sand Pine, Developed, Bare Land, and Water. The Hardwood state encompasses stands in which the canopy is composed of hardwood species and may never revert to a pine state even with aggressive management (e.g., certain riparian zones). Stands that contain a mixture of pine and hardwood trees are included in the Mixed state. The Sand Pine state describes stands that were once dominated by longleaf pine but, because they are adjacent to sand pine seed sources and fire has been suppressed there, have been invaded by sand pine, resulting in an altered fire regime. Developed areas describe stands that have been clear-cut, paved, or heavily altered for human use. The Bare Land state includes areas with exposed soil throughout the base, including the shoreline. Finally, the Water state describes areas covered by water bodies. These landcover types are prevalent on Eglin AFB as

well as in other regions where RCWs are found. These states can contain stands or areas of any age. We did not include separate successional classes for these states as we did with the Longleaf Pine states because, in some instances, successional states do not occur (Developed, Water, Bare Land) or because, in other instances, RCWs rarely use these landcover types no matter the successional state (Hardwood, Mixed, Sand Pine; Bradshaw 1995; Hardesty et al. 1997; Hooper & Lennartz 1981; Porter & Labisky 1986; Repasky 1984). In addition, it was important to include these unsuitable states because RCW habitat could be converted to these other states through long-term successional processes or through immediate human modification to the landscape, which could have important consequences for RCW populations.

To parameterize these landscape states, click on the "States" tab in the "Project Definitions" window. Then click on "Cover Type" and add the cover types shown in Table D-1.3 (to add a description to each cover type, right-click on the box at the top-left corner of the table, and select "Description").

Table D-1.3 Cover types included in the model (and added in the Project Definitions window).

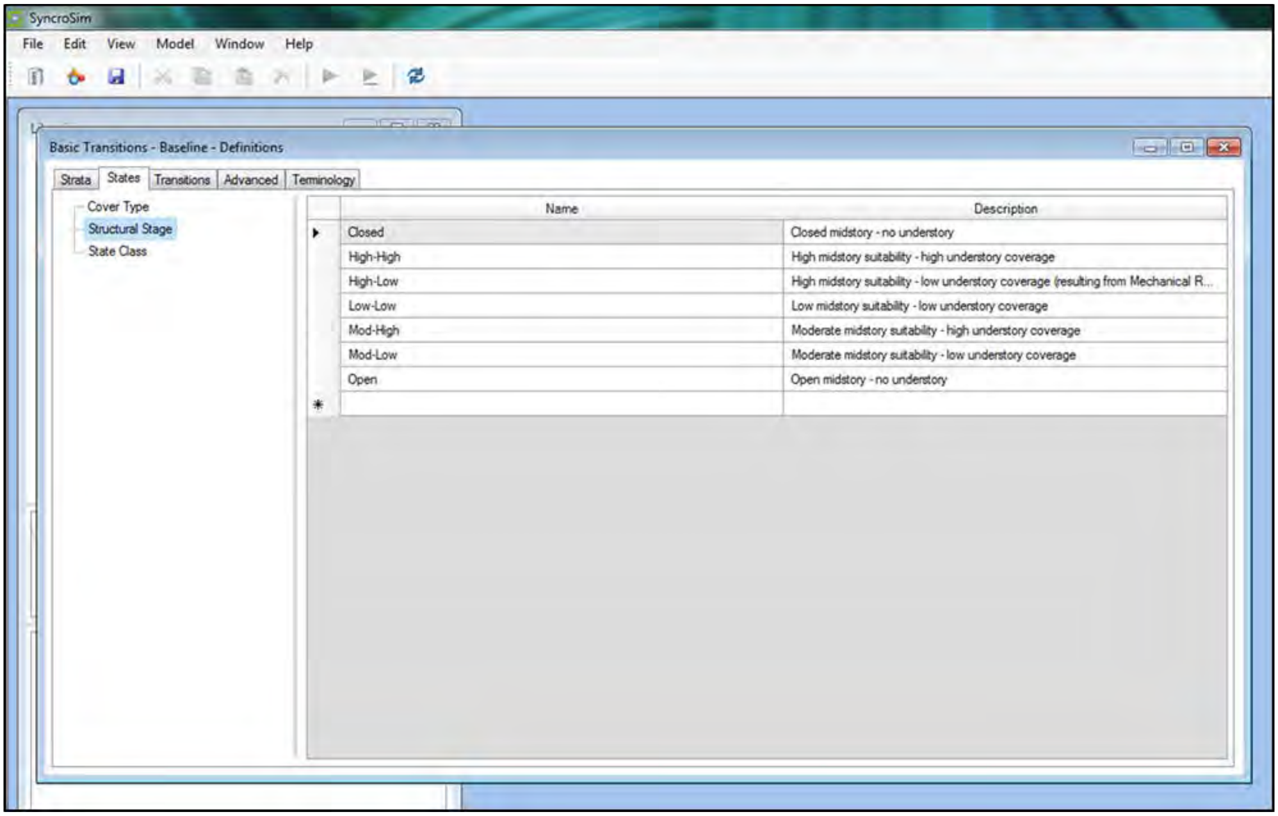
Cover Type	**Description**
Bare Land	Areas with exposed soil
Developed	Developed for human use
Hardwood	Hardwood forest
LLP15-HighCanBA	Longleaf pine 15-59 years – high canopy BA
LLP15-LowCanBA	Longleaf pine 15-59 years – low canopy BA
LLP15-SuitCanBA	Longleaf pine 15-59 years – suitable canopy BA
LLP60-HighCanBA	Longleaf pine $\geq$ 60 years – high canopy BA
LLP60-LowCanBA	Longleaf pine $\geq$ 60 years – low canopy BA
LLP60-SuitCanBA	Longleaf pine $\geq$ 60 years – suitable canopy BA
Mixed	Mixed pine and hardwood stands
Sand Pine	Areas invaded by sand pine
Water	Water bodies
Young Pine	Pine < 15 years



Then, click on "Structural Stage" and add the descriptors for midstory suitability and understory cover shown in Table D-1.4 (to add a description to each structural stage, right-click on the box at the top-left corner of the table, and select "Description").

Table D-1.4 Structural stages included in the model (added in the Project Definitions window).

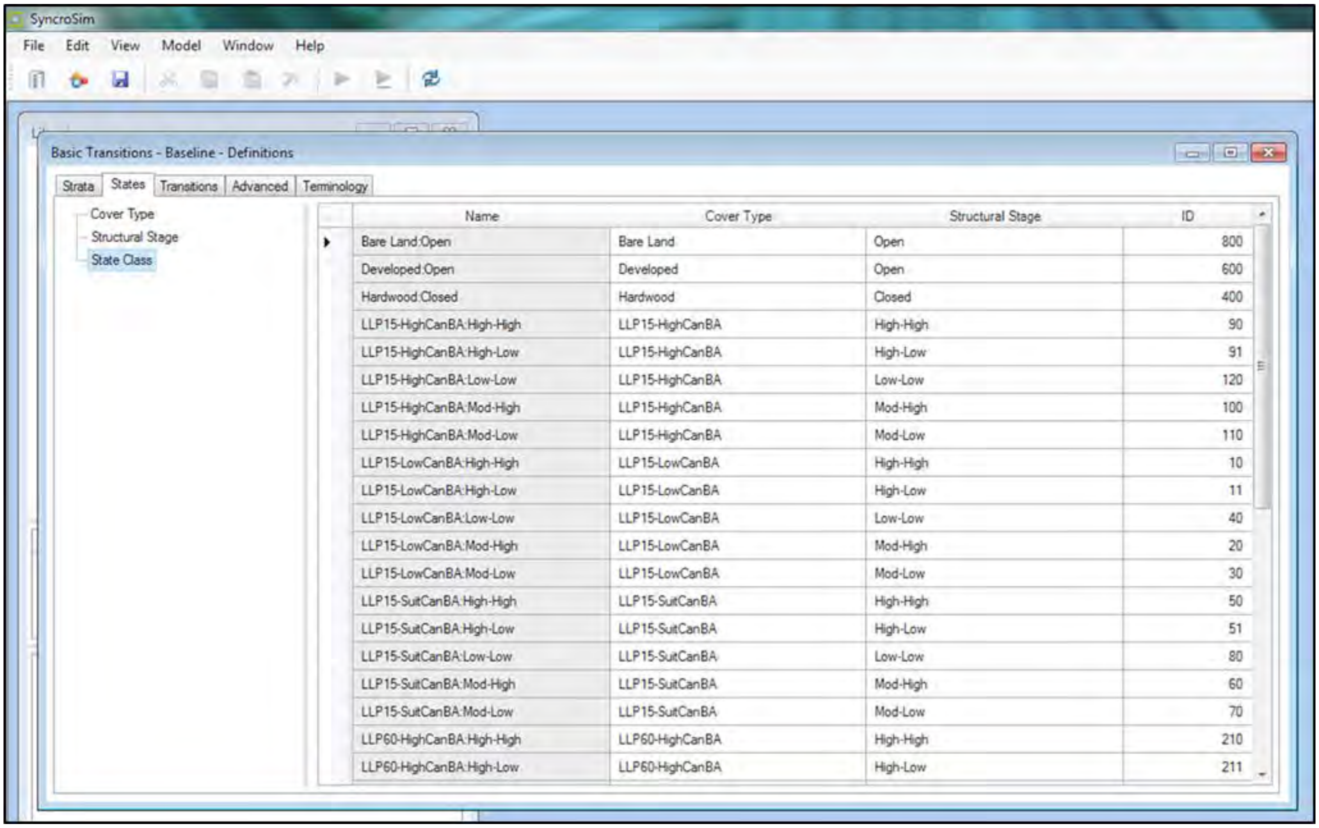
Structural Stage	**Description**
Closed	Closed midstory – no understory
Open	No midstory – no understory
High-High	High midstory suitability – high understory coverage
High-Low	High midstory suitability – low understory coverage
Mod-High	Moderate midstory suitability – high understory coverage
Mod-Low	Moderate midstory suitability – low understory coverage
Low-Low	Low midstory suitability – low understory coverage



The cover types and structural stages can then be linked to create the discrete landscape state classes by clicking "State Class" under the "States" tab in the "Project Definitions" window. Under "State Label X" choose a cover type and, under "State Label Y", choose a structural type to create the landscape state classes with associated ID values shown in Table D-1.5 (to add a column for "ID" values, right-click on the cell at the top-left corner of the table, and select "ID"). The IDs given to each state class are critical to maintaining a functional linkage between the ST-SIM model and the RCW population model; the RCW population model recognizes the suitability of these state classes based on this ID value alone. Therefore, these ID values should not be altered.

Table D-1.5 State classes, which combine the cover types and structural stages shown in Tables D-1.3 and D-1.4, included in the model (added in the Project Definitions window).

State Class	Cover Type	Structural Stage	ID
LLP15-LowCanBA:High-High	LLP15-LowCanBA	High-High	10
LLP15-LowCanBA:High-Low	LLP15-LowCanBA	High-Low	11
LLP15-LowCanBA:Mod-High	LLP15-LowCanBA	Mod-High	20
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA	Mod-Low	30
LLP15-LowCanBA:Low-Low	LLP15-LowCanBA	Low-Low	40
LLP15-SuitCanBA:High-High	LLP15-SuitCanBA	High-High	50
LLP15-SuitCanBA:High-Low	LLP15-SuitCanBA	High-Low	51
LLP15-SuitCanBA:Mod-High	LLP15-SuitCanBA	Mod-High	60
LLP15-SuitCanBA:Mod-Low	LLP15-SuitCanBA	Mod-Low	70
LLP15-SuitCanBA:Low-Low	LLP15-SuitCanBA	Low-Low	80
LLP15-HighCanBA:High-High	LLP15-HighCanBA	High-High	90
LLP15-HighCanBA:High-Low	LLP15-HighCanBA	High-Low	91
LLP15-HighCanBA:Mod-High	LLP15-HighCanBA	Mod-High	100
LLP15-HighCanBA:Mod-Low	LLP15-HighCanBA	Mod-Low	110
LLP15-HighCanBA:Low-Low	LLP15-HighCanBA	Low-Low	120
LLP60-LowCanBA:High-High	LLP60-LowCanBA	High-High	130
LLP60-LowCanBA:High-Low	LLP60-LowCanBA	High-Low	131
LLP60-LowCanBA:Mod-High	LLP60-LowCanBA	Mod-High	140
LLP60-LowCanBA:Mod-Low	LLP60-LowCanBA	Mod-Low	150
LLP60-LowCanBA:Low-Low	LLP60-LowCanBA	Low-Low	160
LLP60-SuitCanBA:High-High	LLP60-SuitCanBA	High-High	170
LLP60-SuitCanBA:High-Low	LLP60-SuitCanBA	High-Low	171
LLP60-SuitCanBA:Mod-High	LLP60-SuitCanBA	Mod-High	180
LLP60-SuitCanBA:Mod-Low	LLP60-SuitCanBA	Mod-Low	190
LLP60-SuitCanBA:Low-Low	LLP60-SuitCanBA	Low-Low	200
LLP60-HighCanBA:High-High	LLP60-HighCanBA	High-High	210
LLP60-HighCanBA:High-Low	LLP60-HighCanBA	High-Low	211
LLP60-HighCanBA:Mod-High	LLP60-HighCanBA	Mod-High	220
LLP60-HighCanBA:Mod-Low	LLP60-HighCanBA	Mod-Low	230
LLP60-HighCanBA:Low-Low	LLP60-HighCanBA	Low-Low	240
Young Pine:Open	Young Pine	Open	250
Mixed:Closed	Mixed	Closed	300
Hardwood:Closed	Hardwood	Closed	400
Sand Pine:Closed	Sand Pine	Closed	500
Developed:Open	Developed	Open	600
Water:Open	Water	Open	700
Bare Land:Open	Bare Land	Open	800



4.2 Transitions

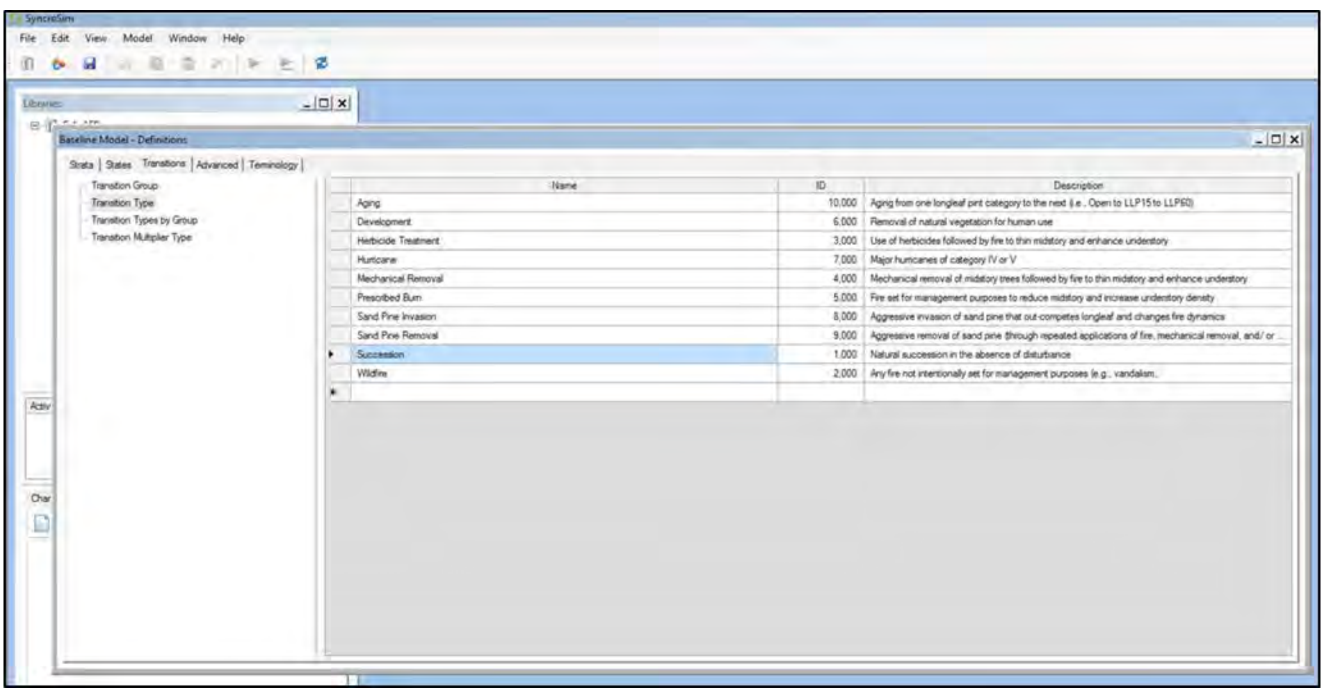
In ST-SIM, discrete landscape cells within the model move from one landscape state to another through probabilistic or deterministic transitions. In our model, those transitions occur through (*i*) natural processes (e.g., succession, aging, natural wildfires), (*ii*) management (e.g., prescribed burns, herbicide treatments, mechanical midstory removal), or (*iii*) other human modification (e.g., development).

The specific parameters for each transition will be added elsewhere, but, for now, the identification and description of each type of transition can be added through the "Project Definitions" window that is accessed by right-clicking on the project name in the "Libraries" window and selecting "Project Definitions". Click on the "Transitions" tab.

First, add each type of transition shown in Table D-1.6 by clicking on "Transition Type" to the left of the "Project Definitions" window and adding each transition type (add columns for "ID" and "Description" by right-clicking on the cell in the top-left corner of the table and selecting "ID" and "Description").

Table D-1.6 Transition types included in the model (added in the Project Definitions window).

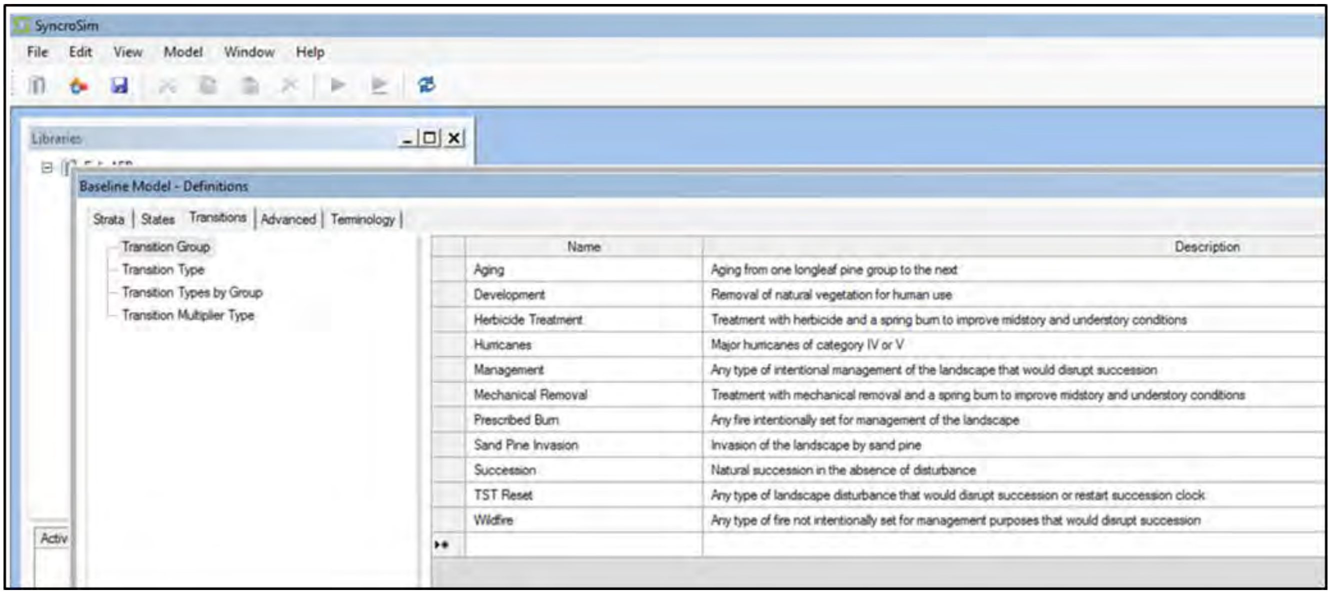
Transition	Description	ID
Aging	Aging from one longleaf pine category to the next (i.e., Open to LLP15 to LLP60)	10,000
Development	Removal of natural vegetation for human use	6,000
Herbicide Treatment	Use of herbicides followed by fire to thin midstory and enhance understory	3,000
Hurricanes	Major hurricanes of category IV or V	7,000
Mechanical Removal	Mechanical removal of midstory trees followed by fire to thin midstory and enhance understory	4,000
Prescribed Burn	Fire set for management purposes to reduce midstory and increase understory density	5,000
Sand Pine Invasion	Aggressive invasion of sand pine that out-competes longleaf and changes fire dynamics	8,000
Sand Pine Removal	Aggressive removal of sand pine (through repeated applications of fire, mechanical removal, and/ or herbicides) to restore stand to longleaf	9,000
Succession	Natural succession in the absence of disturbance	1,000
Wildfire	Any fire not intentionally set for management purposes (e.g., vandalism, lightning strike)	2,000



Each transition type must then be organized into groups for later model parameterization. Create those groups by clicking on “Transition Group” in the “Project Definitions” window and adding the transition groups shown in Table D-1.7.

Status: Transition types included in the model (added in the Project Definitions window).

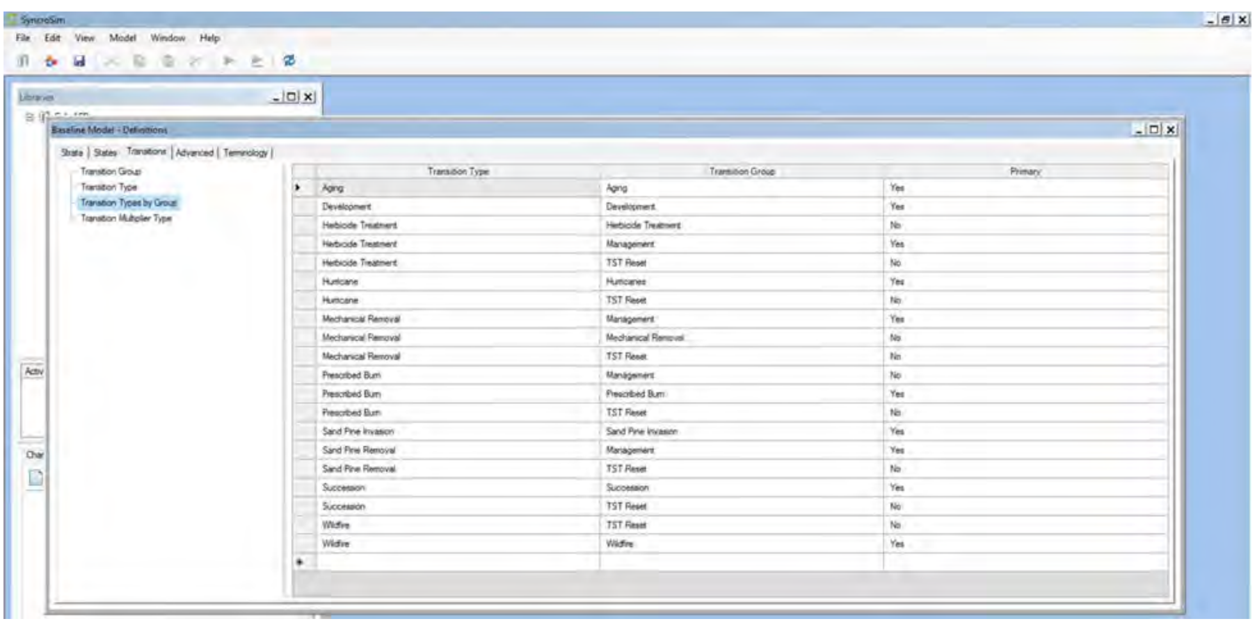
Transition Group	**Description**
Aging	Aging from one longleaf pine category to the next
Development	Removal of natural vegetation for human use
Herbicide Treatment	Use of herbicides followed by fire to thin midstory and enhance understory
Hurricanes	Major hurricanes of category IV or V
Management	Any type of intentional management on the landscape that would disrupt succession
Mechanical Removal	Mechanical removal of midstory trees followed by fire to thin midstory and enhance understory
Prescribed Burn	Fire set for management purposes to reduce midstory and increase understory density
Sand Pine Invasion	Aggressive invasion of sand pine that out-competes longleaf and changes fire dynamics
Succession	Natural succession in the absence of disturbance
Time Since Transition (TST) Reset	Any type of landscape disturbance (including management) that would disrupt succession or restart the succession clock after a landscape cell has advanced by one state on the successional pathway
Wildfire	Any fire not intentionally set for management purposes (e.g., vandalism, lightning strike)



Finally, organize the transition types into groups by clicking on “Transition Type by Group” in the “Project Definitions” window. Right-click in the top left cell in this table, and select “Primary” to add the “Primary” column to this table. Under “Transition Type”, select the specific transition, and, under “Transition Group”, select the group to which it belongs according to Table D-1.8. Each transition group is associated with a single primary group, which is the group for which the model will simulate initiation and spread events. All other groups that a given transition type is associated with are considered secondary and are specified as such under the “Primary” column in this table (Table D-1.8). These secondary groups are used within the model for reporting purposes or to control other transitions such as Succession.

Table D-1.8 Transitions types organized under broader transitions groups.

Transition Type	Transition Group	Primary
Aging	Aging	Yes
Development	Development	Yes
Herbicide Treatment	Herbicide Treatment	No (Secondary)
Herbicide Treatment	Management	Yes
Herbicide Treatment	TST Reset	No (Secondary)
Hurricane	Hurricanes	Yes
Hurricane	TST Reset	No (Secondary)
Mechanical Removal	Management	Yes
Mechanical Removal	Mechanical Removal	No (Secondary)
Mechanical Removal	TST Reset	No (Secondary)
Prescribed Burn	Management	No (Secondary)
Prescribed Burn	Prescribed Burn	Yes
Prescribed Burn	TST Reset	No (Secondary)
Sand Pine Invasion	Sand Pine Invasion	Yes
Sand Pine Removal	Management	Yes
Sand Pine Removal	TST Reset	No (Secondary)
Succession	Succession	Yes
Succession	TST Reset	No (Secondary)
Wildfire	TST Reset	No (Secondary)
Wildfire	Wildfire	Yes



Further descriptions of each transition type and the use of the transition groupings will be explained in subsequent sections. At this point, save the project and close the “Project Definitions” window.

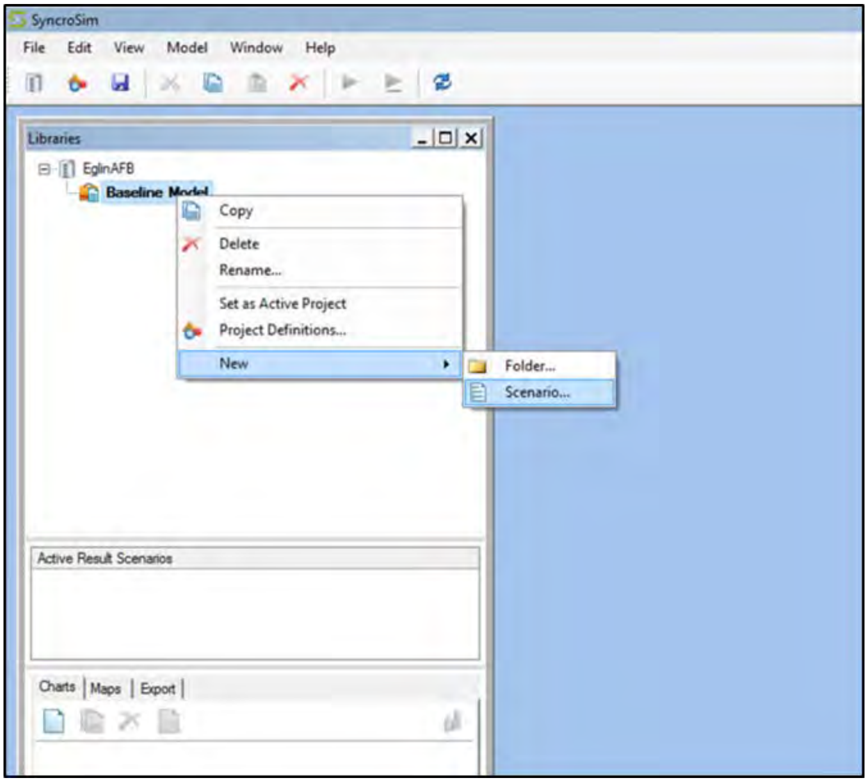
4.3 Organization of States and Transitions

Landscape cells within the ST-SIM model move from one landscape state to another through probabilistic or deterministic transitions. For probabilistic transitions, the user indicates the probability that a specific transition will occur in a given landscape state, with probabilities varying by state according to the characteristics of that state. In large landscapes, such as the Eglin landscape (~ 188,000 ha), this probability typically reflects the percentage of the landscape that will be impacted by a given transition each time step and is dependent on the availability of the landscape states in which that transition is eligible to occur. In contrast, deterministic transitions always occur after some user-specified period of time or event has occurred.

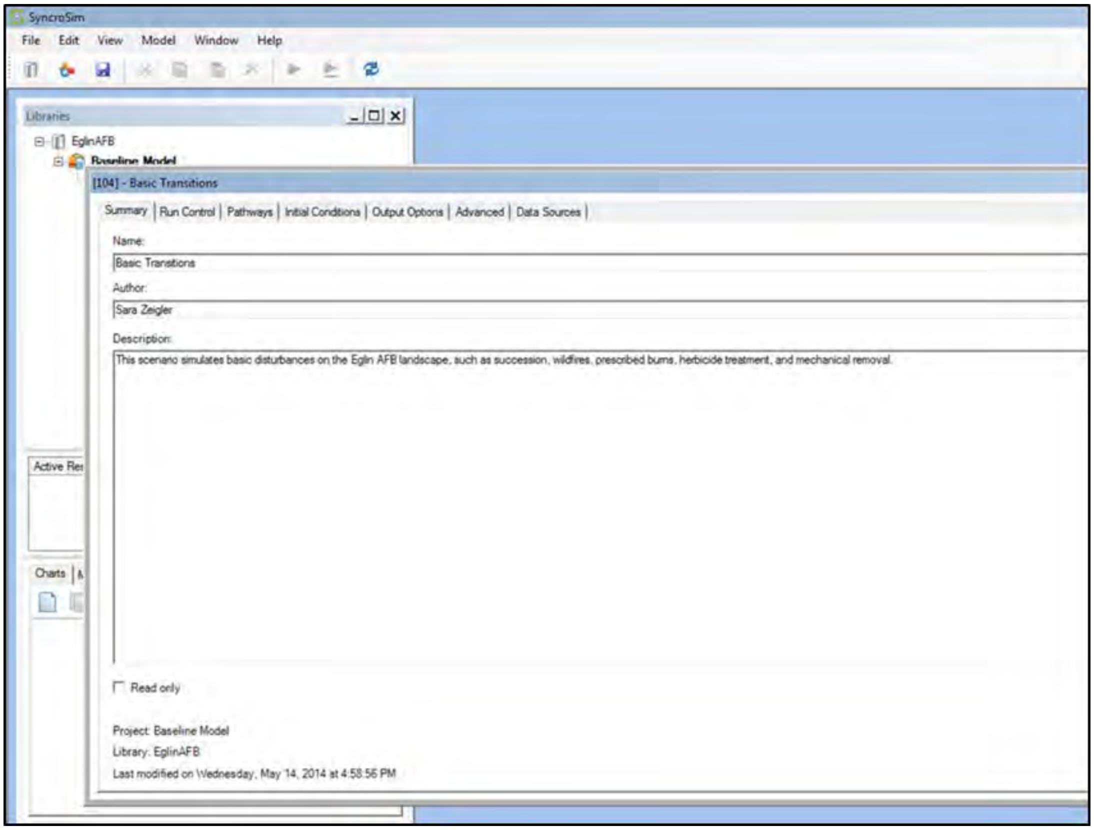
Management transitions, such as Prescribed Burn, Herbicide Treatment, Mechanical Removal, and Sand Pine Removal, have both probabilistic and deterministic elements in their parameterizations. These transitions are probabilistic in that the locations of these actions throughout the study area can occur anywhere in the landscape (as long as the underlying state class is eligible for a given management action). However, we also model management actions as targets (described in *Sections 4.3.3 Fire, 4.3.4 Herbicide Treatment,* and *4.3.5 Mechanical Removal*). This allows the user to specify the area over which each management action will be applied on the landscape.

Although we created transitions for Hurricanes, Sand Pine Invasion, Sand Pine Removal, and Development, we will not apply these transitions in the simple Basic Transitions Scenario described in this section. The applications of some of these more advanced transitions are explained in detail in *Section 7. Advanced Model Parameterization*. Furthermore, the user can force certain transitions, such as the management actions or Development, at exact locations in the landscape. This is also described in more detail in *Section 7.* These more advanced applications of the model were not considered in the initial baseline testing and validation; however, they can be used at the user's discretion to simulate possible management actions and landcover changes to the Eglin AFB landscape.

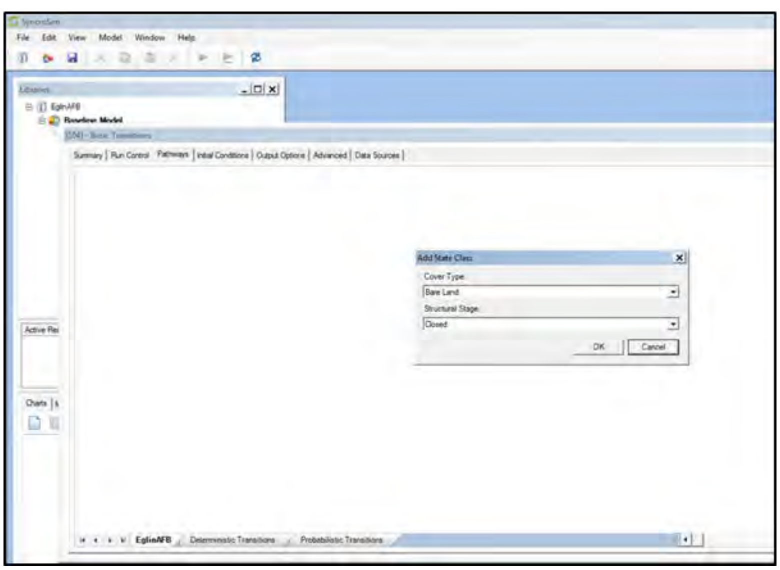
In the remainder of this section, we will describe the transitions that were simulated in the Basic Transitions Scenario in more detail as well as how those transitions link the landscape states. To visually organize landscape state classes and connect those classes through the transitions described in the previous section, begin by creating a new scenario within the main project by right-clicking on the project name ("Baseline Model") in the "Libraries" window and selecting "New" and "Scenario".



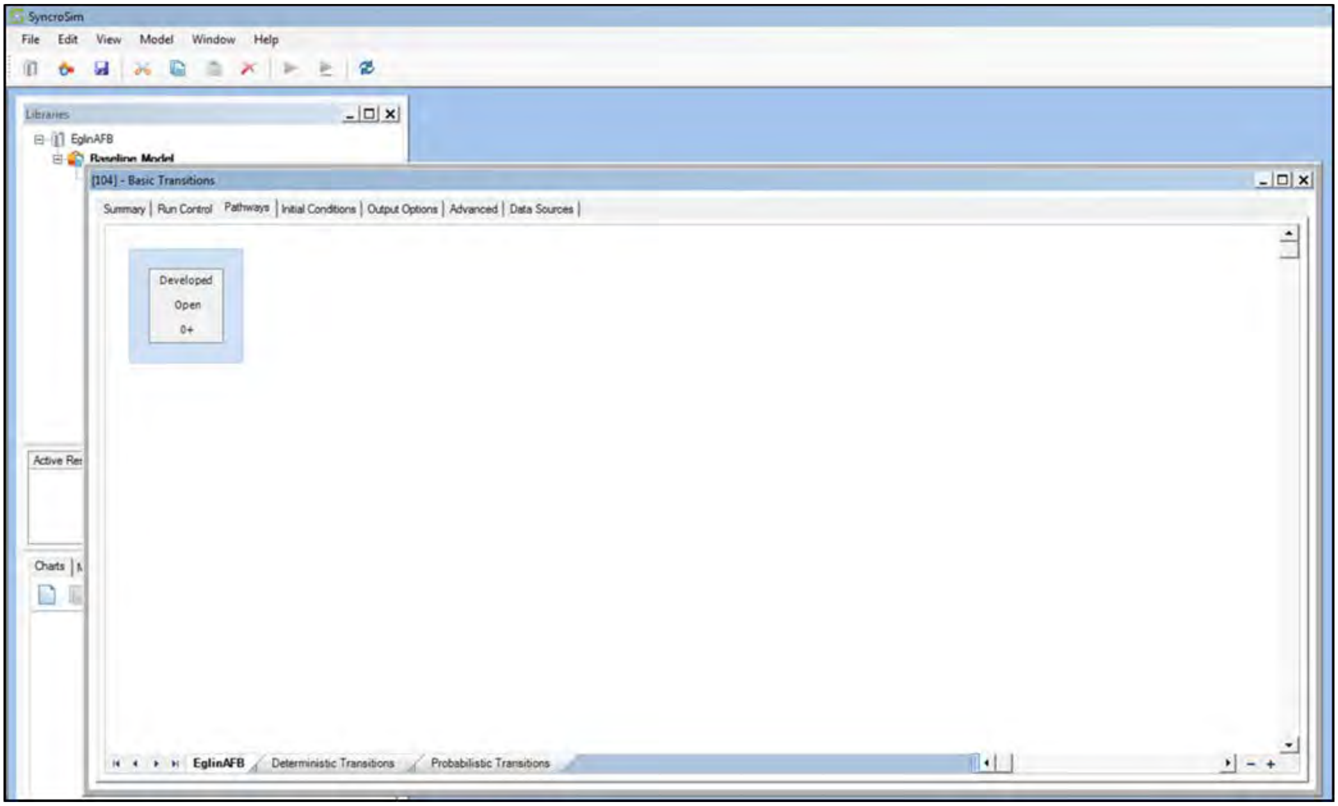
The “New Scenario” window appears, where the user can name the scenario, indicate the author, and add any pertinent information pertaining to the scenario. In this first scenario, we will only be simulating the basic transitions (including Wildfire, Prescribed Burns, Herbicide Treatment, Mechanical Removal, and Succession), so we will name this scenario “Basic Transitions”.



Then, double-click the scenario name in the "Libraries" window to open the scenario's input window. Click on the "Pathways" tab, and select the "EglinAFB" stratum worksheet at the bottom of the window. Right-click anywhere in this window, and select "Add State Class…". The "Add State Class" window will appear where the Cover Type and appropriate Structural Stage can be selected.



Select a Cover Type with its appropriate Structural Stage (e.g., Developed – Open). A small gray box will appear representing the landscape state. This box can be moved and organized based on the user's preference by clicking on the box and dragging it to a more suitable location.



The top line of each box represents the Cover Type, the middle line represents the Structural Stage, and the bottom line represents the Age Class that landscape cells of that Cover and Structural Type must fall within. For the longleaf pine states, the top line represents Canopy BA, the middle line represents Midstory Suitability and Understory Cover, and the bottom line represents Age (Figure D-1.4).

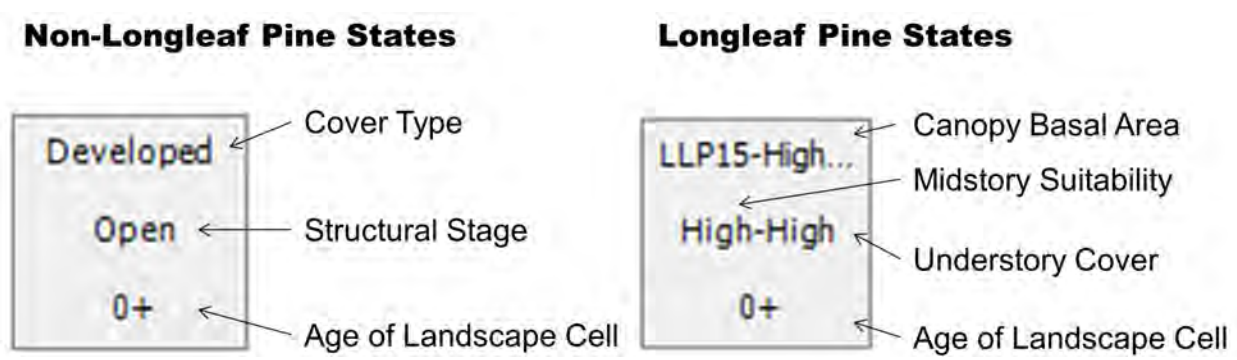
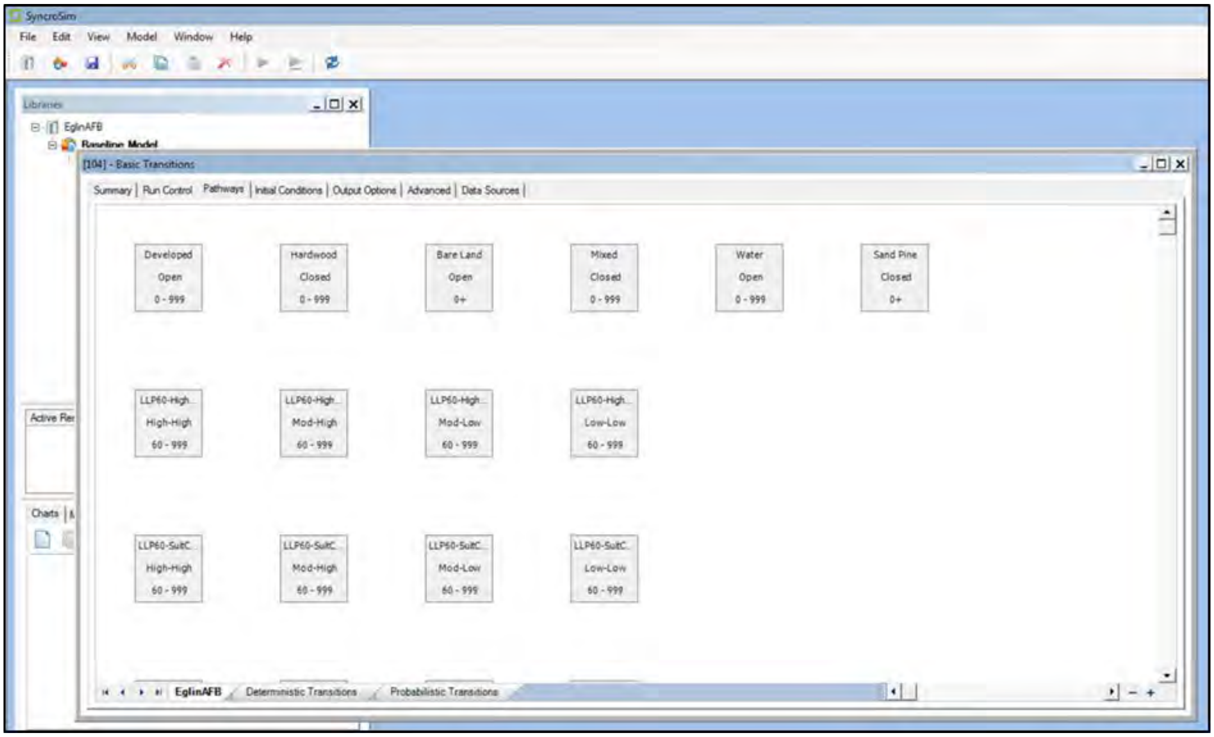
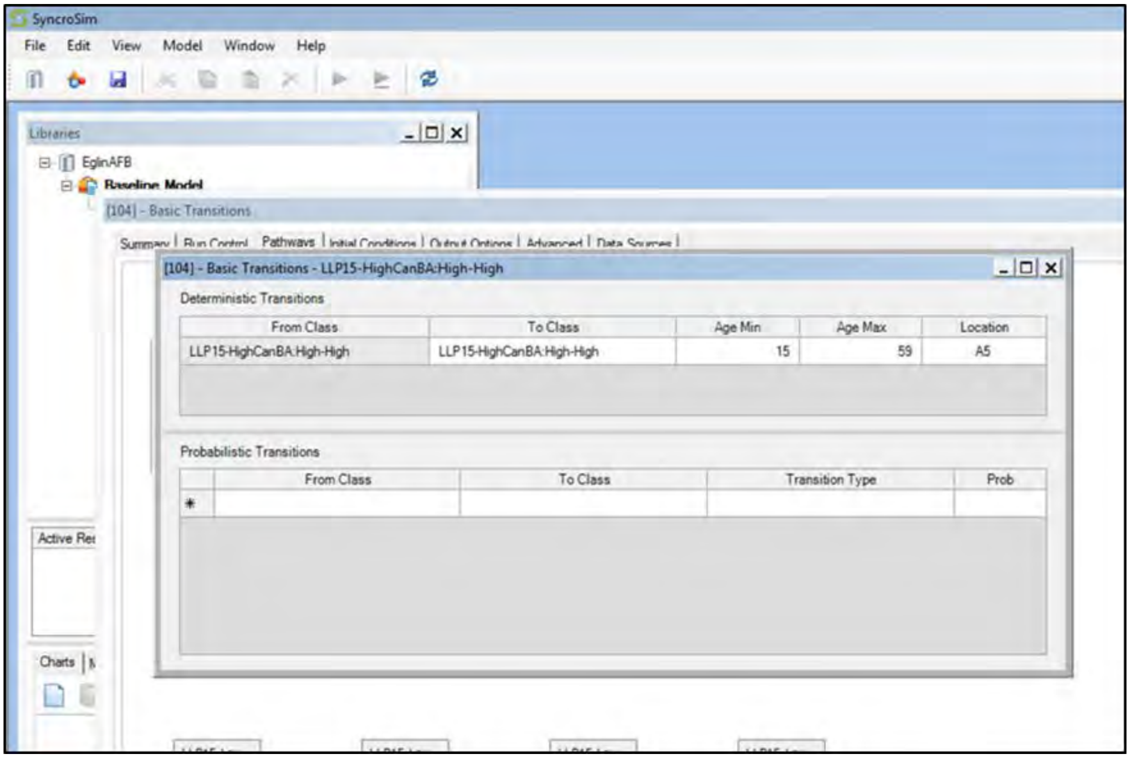


Figure D-1.4 Information contained in the landscape state boxes in ST-SIM.

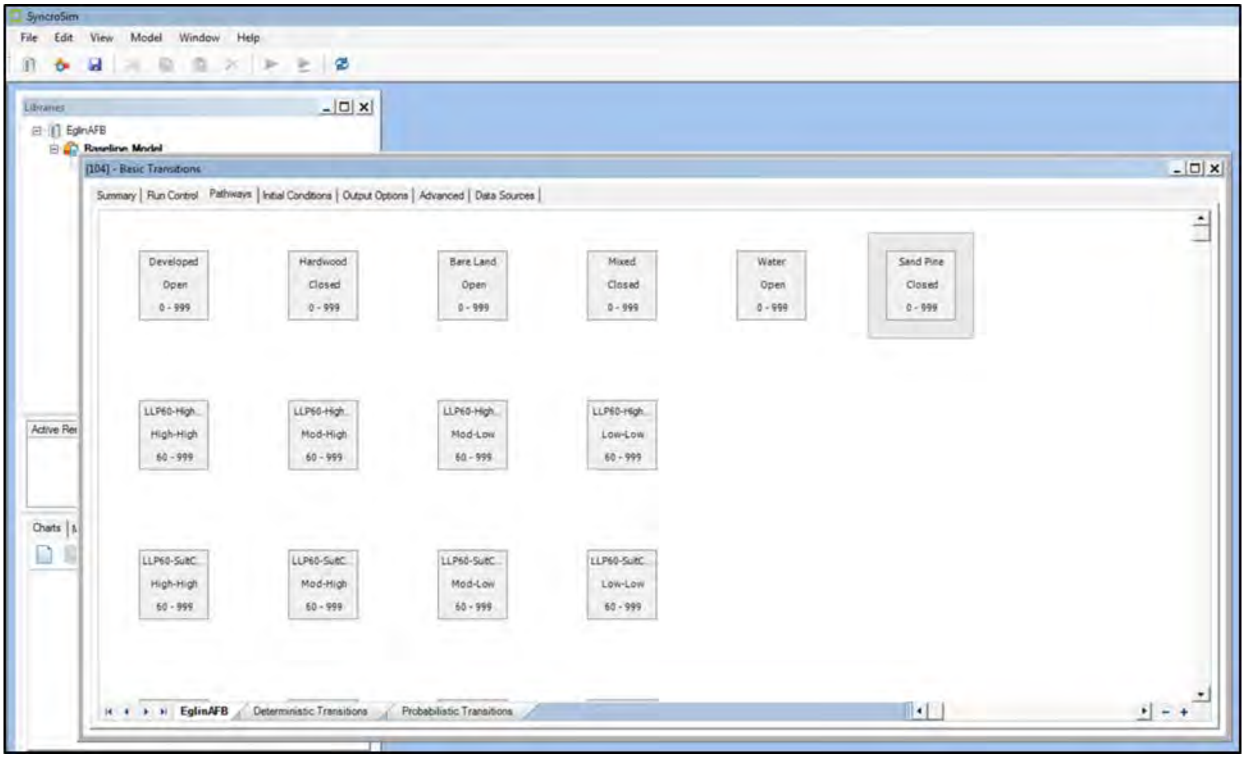
You will repeat the process for adding states until all states described in *Section 4.1 Landscape States* have been added to this screen



As discussed in *Section 4.1 Landscape States*, the longleaf pine states are further differentiated by stand age. Thus, stands must be 60 years or older to exist in a Longleaf Pine ≥ 60 state (LLP60), stands must be between 15 and 59 years old to exist in a Longleaf Pine ≥ 15 state (LLP15), and stands must be < 15 years old to exist in the Young Pine state. To add an age-limitation to the state class boxes, double-click on a gray state box (for example, the box for LLP15-LowCanBA:High-High). The "Basic Transitions" window for that state class will appear. In the top part of the screen under "Deterministic Transitions", make sure the same state class is selected in the "From Class" and "To Class" dropdown lists (in this example, LLP15-LowCanBA:High-High). Then choose the minimum age and maximum age under "Age Min" and "Age Max", respectively, for that state class. In this example, "15" and "59" would be input for "Age Min" and "Age Max", respectively.



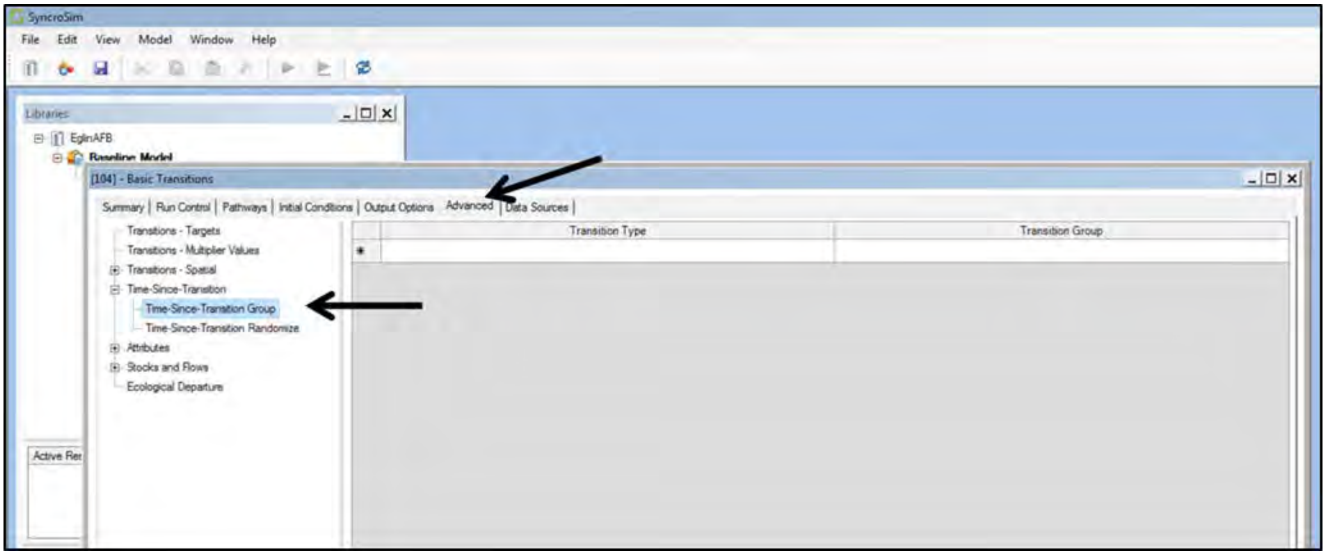
Repeat this process for every state class depicting longleaf pine, where you would choose "15" as the "Age Min" and "59" for "Age Max" for every LLP15 cover type; "60" for "Age Min" and "999" for "Age Max" for every LLP60 cover type; and "0" for "Age Min" and "14" for "Age Max" for the Young Pine cover type. Age is not relevant for the non-longleaf pine states, and the ages for these states can be left as-is. When this step is completed, all state class boxes should have appropriate age ranges along the bottom line.



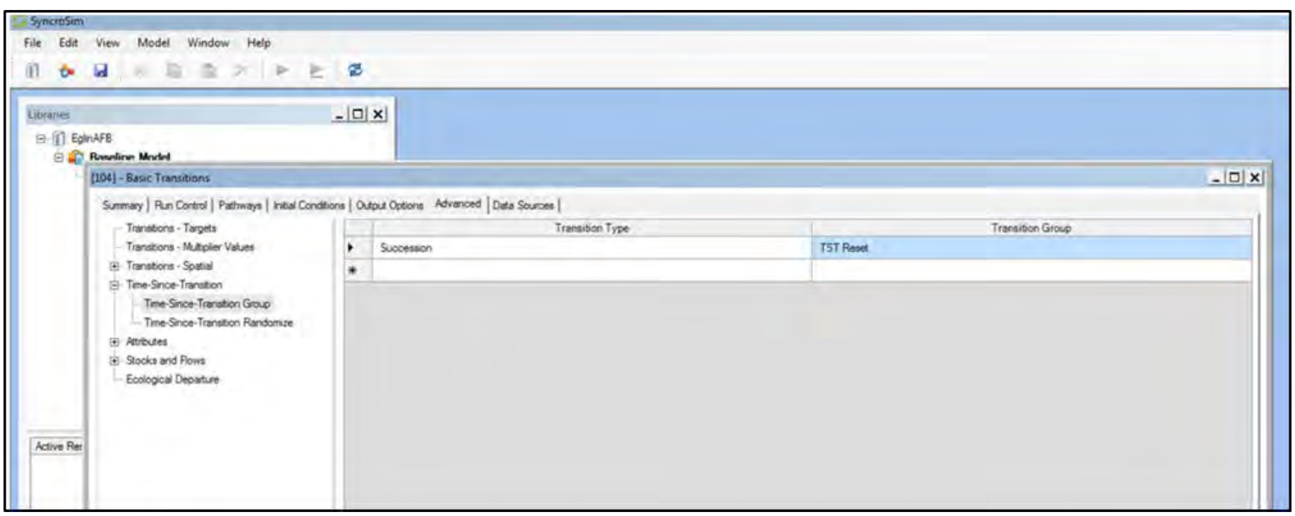
4.3.1 Succession

In the ST-SIM landscape model for Eglin, we assumed that it would take 5-, 15-, or 20-year increments of fire suppression to alter midstory and understory conditions enough to warrant a change in successional state but that canopy BA would not change over such short time scales (Figure D-1.2). Thus, for example, a stand that has a suitable canopy BA, high midstory suitability, and high percentage understory cover would move to the next successional state (suitable canopy BA, moderate midstory suitability, and high percentage understory cover) if fire did not occur in that stand within 15 years. If another 5 years progress without fire, the stand would move from that new state to the state characterized by suitable canopy BA, moderate midstory suitability, and low percentage understory cover as understory plants begin to suffer from competition with the growing midstory (and so on; Figure D-1.2). We did not include successional transitions from lower canopy BAs to higher canopy BAs. Such transitions could occur after many years of fire suppression (e.g., >> 40 years; Veno 1976), which is beyond the temporal scope of the RCW population model (maximum time scale of 50 years). If the ST-SIM landscape model is extended beyond 50 years, it may be appropriate to include these successional transitions. However, we did assume that a longleaf pine stand with a high BA would succeed to the Mixed landscape state after additional 20 years of fire suppression (55 total years of fire suppression; Figure D-1.2).

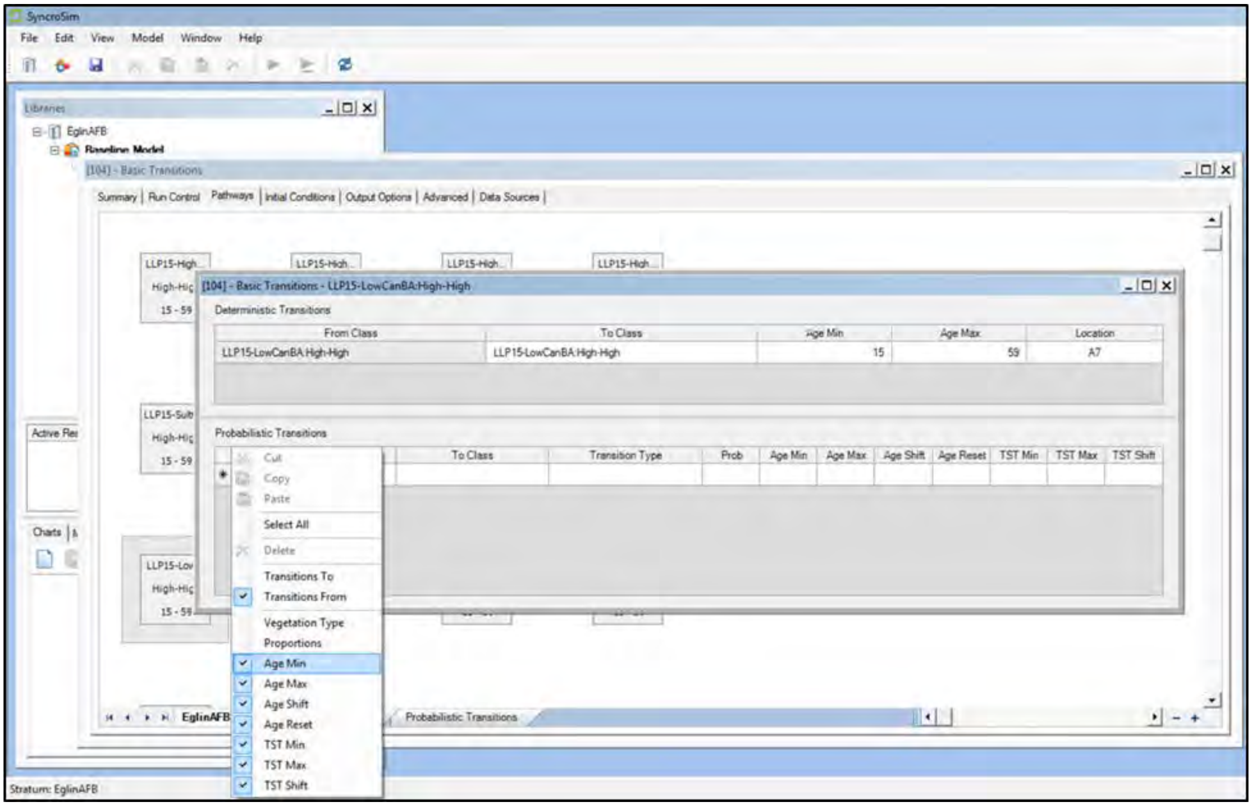
In this model of longleaf pine dynamics, we assume that succession only occurs in the absence of management and disturbances. To create this condition in ST-SIM, go to the “Advanced” tab in the “Basic Transitions” window for this scenario, click the “+” icon next to “Time-Since-Transition” in the list on the left side of this screen, and select “Time-Since-Transition Group”.



Then, select “Succession” under “Transition Type”, and “TST Reset” under “Transition Group”. By creating this parameter in ST-SIM, succession cannot occur unless a user-specified number of years have passed without a transition in the group “TST Reset” occurring (see section *4.2 Transitions*). This parameter also controls how long a landscape cell will remain in a given state before it proceeds to the next state through succession. For example, if a landscape cell in the state LLP15-HighCanBA:High-High shifts to the state LLP15-HighCanBA:Mod-High after not experiencing a disturbance for 15 years, the succession “clock” will restart back to zero. The cell will then only proceed to LLP15-HighCanBA:Mod-Low if a disturbance does not occur for 5 years.

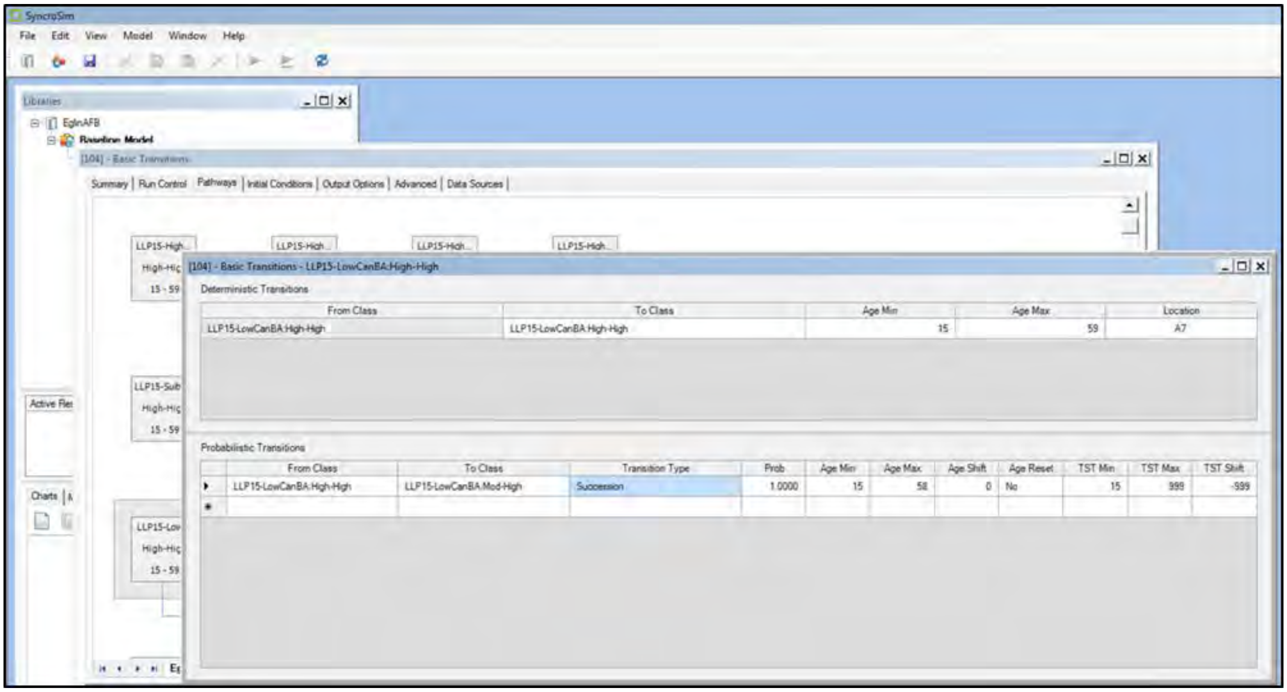


To specify the successional transitions, go back to the “Pathways” tab in the “Basic Transitions” window, and double click on a gray state class box for a Longleaf Pine state (for example, LLP15-LowCanBA:High-High). The “Basic Transitions” window specific to this state class will appear. Right-click on the blank top-left corner of the table under “Probabilistic Transitions”, and select all options for “TST” and “Ages” from this dropdown menu.



A total of 11 columns should now appear in the “Probabilistic Transitions” table in this window. In the “From Class” dropdown under “Probabilistic Transitions”, select the state class to which this window belongs (in this example, “LLP15-LowCanBA:High-High”). Under “To Class”, select the state class that, in Figure D-1.2, is in the same row and one box to the right (in this example, “LLP15-LowCanBA:Mod-High”). Select “Succession” under “Transition Type”, and input “1” under “Prob”.

In this example and for all other LLP15 states, select “15” as the “Age Min” and “58” as the “Age Max” (this will be explained in detail later). Select “60” as the “Age Min” and “999” as the “Age Max” for all LLP60 states. Input “0” under “Age Shift” and “No” under “Age Reset”. Finally, select the minimum number of years that would have to go by without disturbance for this state class to succeed to the next under “TST Min” (in this example, “15”), and input “999” and “-999” under “TST Max” and “TST Shift”, respectively. In this example, these inputs specify that a landscape cell containing a longleaf pine stand that is between 15 and 58 years old in the state class LLP15-LowCanBA:High-High will move to state class LLP15-LowCanBA:Mod-High through succession with certainty if no disturbance occurs after 15 years. When this happens, the age of the stand (or landscape cell) will not reset to 0 and it will not change (however, the age will progress by 1 year at the end of the time step).

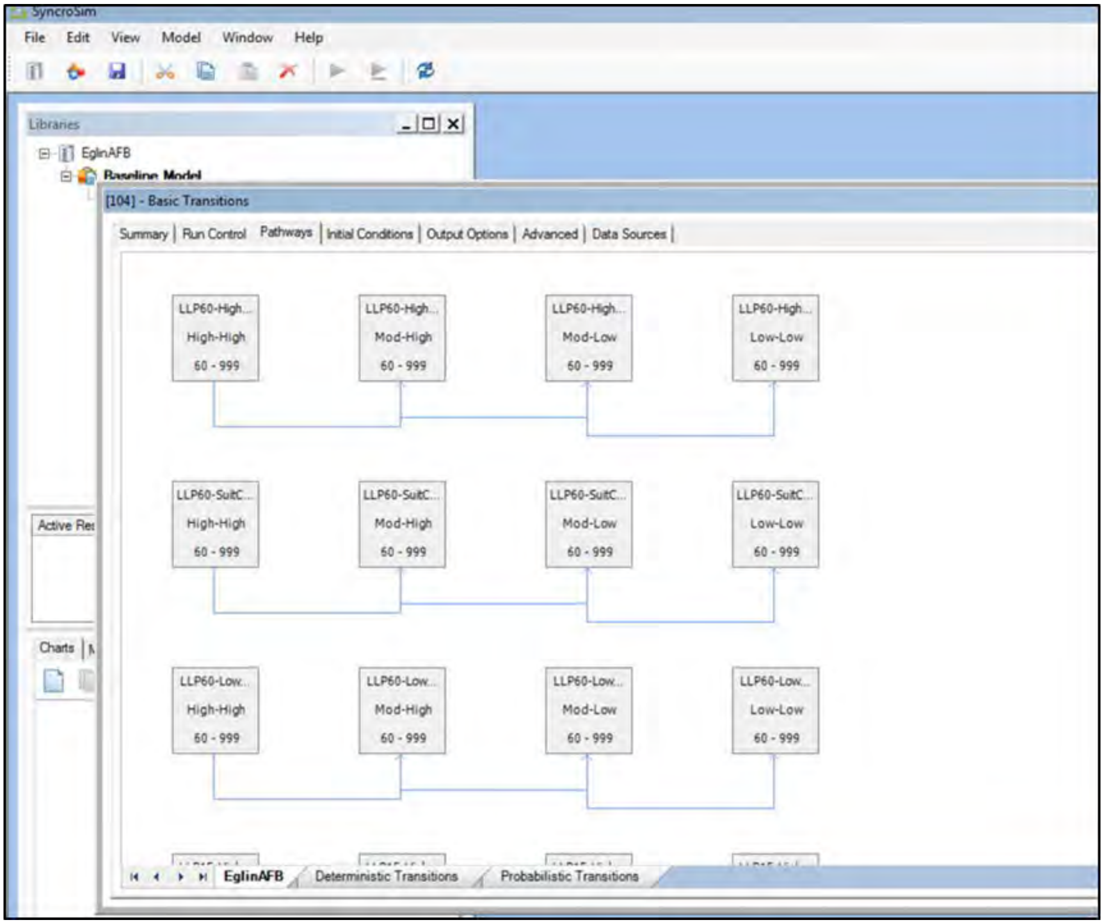


You will repeat this process for all other longleaf pine states such that a state class moves to the class in the same row and one box to the right of the original state class (with the exception of High-Low landscape states, which shift two states to the right; Figure D-1.2). You will always input "Succession" for "Transition Type", "1" for "Prob", "0" for "Age Shift", "No" for "Age Shift", "999" for "TST Max", and "-999" for "TST Shift", regardless of the original state class. "Age Min" and "Age Max" will vary according to the original state's required age range (for example, these values will be "15" and "58" for any LLP15 Cover Type, "60" and "999" for any LLP60 Cover Type, and "0" and "14" for the Young Pine state). Finally, "TST Min" will also vary depending on the Structural Stage of the original state class (also see Figure D-1.2):

1. High-High to Mod-High requires 15 years without disturbance ("TST Min" = 15)
2. High-Low to Mod-Low requires 20 years without disturbance ("TST Min" = 20)
3. Mod-High to Mod-Low requires 5 years without disturbance ("TST Min" = 5)
4. Mod-Low to Low-Low require 15 years without disturbance ("TST Min" = 15)

(Note, the longleaf pine state classes characterized by High Midstory Suitability and Low Understory Cover are a special state added to reflect the habitat conditions following the use of herbicide or mechanical midstory removal. These states, not shown in the screen shot, will proceed to the equivalent cover type with Moderate Midstory Suitability and Low Understory Cover following 20 years without burning or other management. See Figure D-1.2 and *Sections 4.3.4 Herbicide Treatment* and *4.3.5 Mechanical Removal* for more information.).

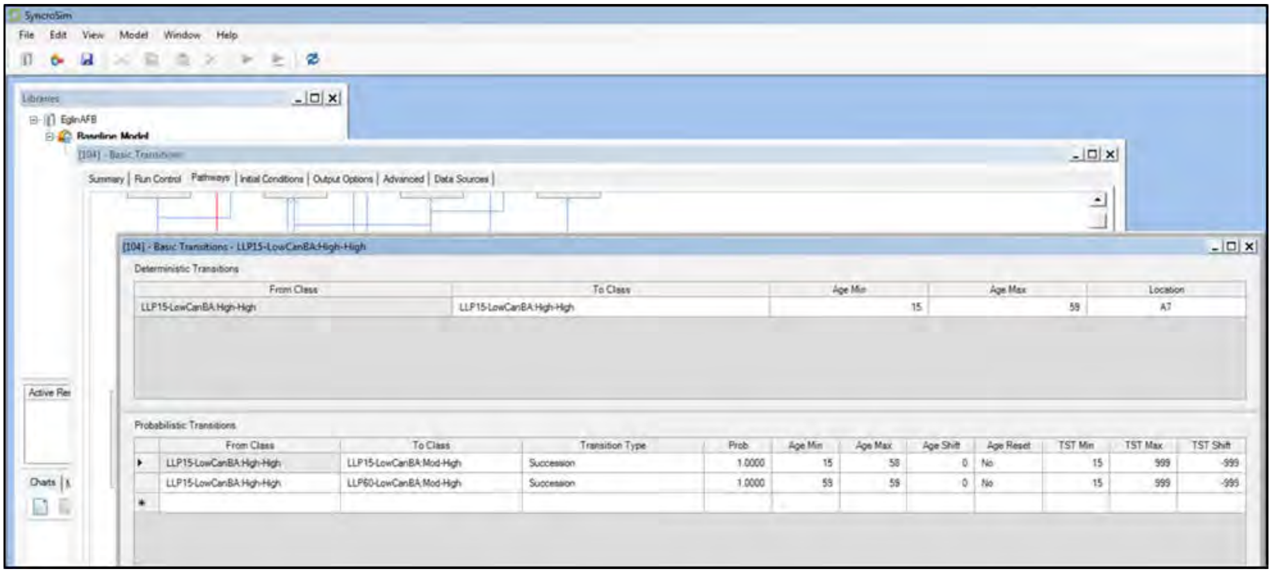
After you have repeated this process, each longleaf pine landscape state should be linked to the state directly to its right through succession.



You will also include a second Succession transition for all LLP15 Longleaf Pine states to account for both aging and succession. As described in section *4.3.2 Aging,* a landscape cell/stand that is 59 years old will age up to an LLP60 Longleaf Pine state in the next time step. When a landscape cell happens to cross both the age threshold (i.e., 59 years to 60 years) and the time without disturbance threshold (i.e., 15 or 5 years) in the same time step, then the landscape cell will transition according to both aging and succession rules.

To parameterize this transition, double-click on a gray state box in the “Pathways” tab in the “Basic Transitions” window (for example, LLP15-LowCanBA:High-High). You may need to make the “TST” and “Ages” columns reappear in the “Probabilistic” table in the state class window. Under “To Class” in the second row of this table, select the state class that is one box to the right (or two boxes to the right for High-Low landscape states) of the equivalent state class in the LLP60 Longleaf Pine class in Figure D-1.2 (in this example, LLP60-LowCanBA:Mod-High). Select “Succession” in the “Transition Type” drop-down. Input “59” for both the “Age Min” and “Age Max”, “0” under “Age Shift”, and “No” under “Age Reset”. Finally, select the minimum number of years that must go by without a disturbance for this state class to succeed to the next under “TST Min” (in this example, “15”), and select “999” and “-999” under “TST Max” and “TST Shift”, respectively. In this example, these inputs specify that a landscape cell at age 59 years old in state class LLP15-LowCanBA:High-High will move to state class LLP60-LowCanBA:Mod-High at the next time step through succession with certainty if no disturbance occurs after 15 years. When this happens, the age of the stand (or landscape cell) will not reset to

0 (however, the age will progress by 1 year at the end of the time step). This process should be repeated for all LLP15 Longleaf Pine states.



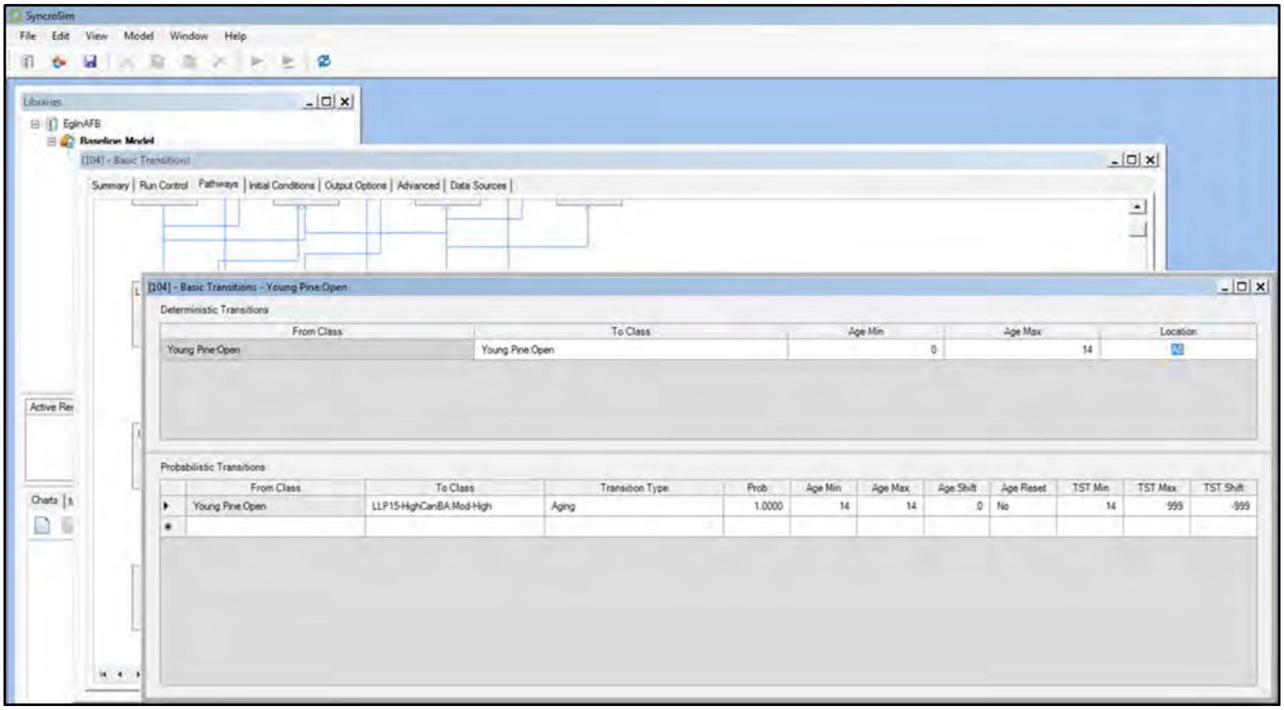
Finally, link the LLP60-HighCanBA:Low-Low state to the Mixed state through succession by double-clicking on the state's gray state box in the "Pathways" tab in the "Basic Transitions" window and selecting "Mixed:Closed" under "To Class". Select "Succession" in the "Transition Type" drop-down. Input "60" and "999" for "Age Min" and "Age Max", respectively. Input "0" under "Age Shift", "No" under "Age Reset", "20" under "TST Min", and "999" and "-999" under "TST Max" and "TST Shift", respectively. Here, these inputs specify that a landscape cell in the LLP60-HighCanBA:Low-Low state class will transform to a Mixed hardwood/pine stand through succession with certainty if no disturbance occurs after 20 years. When this happens, the age of the stand (or landscape cell) will not reset to 0 (however, the age will progress by 1 year at the end of the time step).

State classes for Sand Pine, Bare Land, Developed, Water, Hardwood, Mixed, Young Pine, and any other longleaf pine state with the Low-Low Structural Stage should not be linked to any other state class through succession, and this transition will not be added to the "Basic Definitions" window for these states.

4.3.2 Aging

The ages of stands (or landscape cells) are tracked within ST-SIM simulations because tree age is important for RCW habitat suitability. The age of the oldest tree cohort for stands throughout Eglin AFB is known from a 2005 GIS – based stand inventory. During a simulation, stands will age by one year with each model time step. If the age of a stand containing longleaf pine progresses from 14 to 15 years, the stand's state will move from the Young Pine state to the state characterized by Longleaf Pine 15-59 years, high canopy BA, moderate midstory suitability, and high understory cover (reflective of the successional pathway for plantation pine stands). To add this transition to the Young Pine state class in the model, double-click on the gray Young Pine state box under the "Pathways" tab of the "Basic Transitions" scenario window. Add columns for "Age" and "TST" to the "Probabilistic Transitions" table in this window. Select "Young Pine" under the "From Class" column and "LLP15-HighCanBA:Mod-

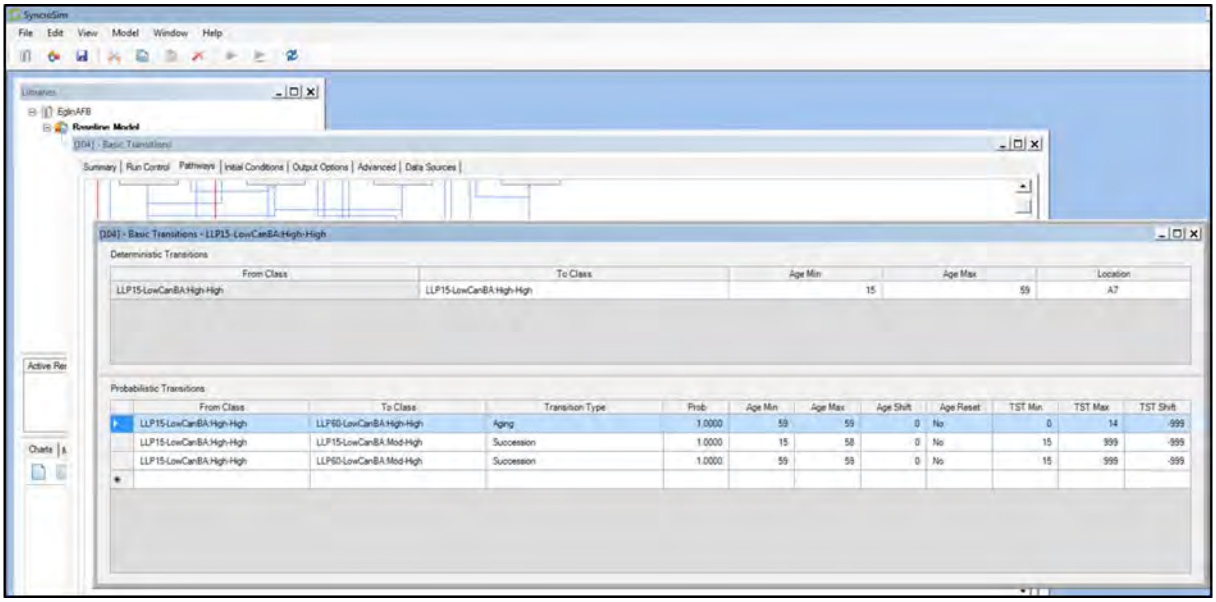
High" under the "To Class" column. For "Transition Type", select "Aging". Then, input "1" under "Prob", "14" under both "Age Min" and "Age Max", "0" under "Age Shift", "No" under "Age Reset", "14" under "TST Min", and "999" under "TST Max". This parameterization indicates that a landscape cell at 14 years of age in the Young Pine state class will progress to the Longleaf Pine 15-59 years state with high canopy BA, moderate midstory suitability, and high understory cover with certainty if no disturbances have occurred within the last 14 years. At this point, age will continue to advance to age 15 (i.e., it will not reset to 0).



Likewise, if a stand's age progresses from 59 to 60 years for a longleaf pine state during the course of a simulation, then the stand will move from the successional state within the Longleaf Pine 15-59 years class to the corresponding successional state within the Longleaf Pine ≥ 60 years class (Figure D-1.2). (Note, if the successional threshold and age threshold are crossed in the same time step for any Longleaf Pine 15-59 state, then the primary transition is for Succession, and this parameterization is explained in section *4.3.1 Succession*).

To add a transition for Aging, double-click on the gray state box for an LLP15 state (for example, LLP15-LowCanBA:High-High) under the "Pathways" tab of the "Basic Transitions" scenario window. Add columns for "Age" and "TST" to the "Probabilistic Transitions" table in this window. Select the current state class (in this example, "LLP15-LowCanBA:High-High") under the "From Class" column and the equivalent class in the LLP60 Longleaf Pine grouping (in this example, "LLP60-LowCanBA:High-High") under the "To Class" column. For "Transition Type", select "Aging". Then, input "1" under "Prob", "59" under both "Age Min" and "Age Max", "0" under "Age Shift", "No" under "Age Reset", "0" under "TST Min" and "14" under "TST Max", and "-999" under "TST Shift". This parameterization indicates that a longleaf pine landscape cell at 59 years of age will progress to the same Cover Type and Structural Class in the Longleaf Pine ≥ 60 years grouping at the next time step with 100% probability if there has been less than 15 years since the last disturbance. At this point, age will

advance to age 60 (i.e., it will not reset to 0). Remember, if the landscape cell is 59 years of age and it has been 15 years since the last disturbance, this cell will both age and be impacted by succession (described in *4.3.1 Succession*).



This process should be repeated for all LLP15 Longleaf Pine states. When you are finished, each LLP15 Longleaf Pine state (except for the states with low midstory suitability and low ground cover) should now be connected to three states: two through succession and one through aging. Because aging does not impact the characteristics of any other state class (LLP60 states, Mixed, Hardwood, Sand Pine, Bare Land, Water, or Developed), we did not add an Aging transition to any of these states. Thus, these states should not be connected to any other state through aging.

4.3.3 Fire

The longleaf pine ecosystem is highly adapted to and dependent on fire. In the ST-SIM model, we assumed that fires would occur at high or low intensities depending on the preceding period of fire suppression as reflected in the current state of the stand (Figure D-1.5, Figure D-1.6). Low intensity fires, which occur in states that have been burned within 0-35 years, do not impact the canopy BA but do shift the stand one state to the left in the successional sequence. High intensity fires occur in states that have not been burned in > 35 years and impact canopy BA, midstory suitability, and herbaceous groundcover by moving the state one level below and two states to the left in the successional sequence.

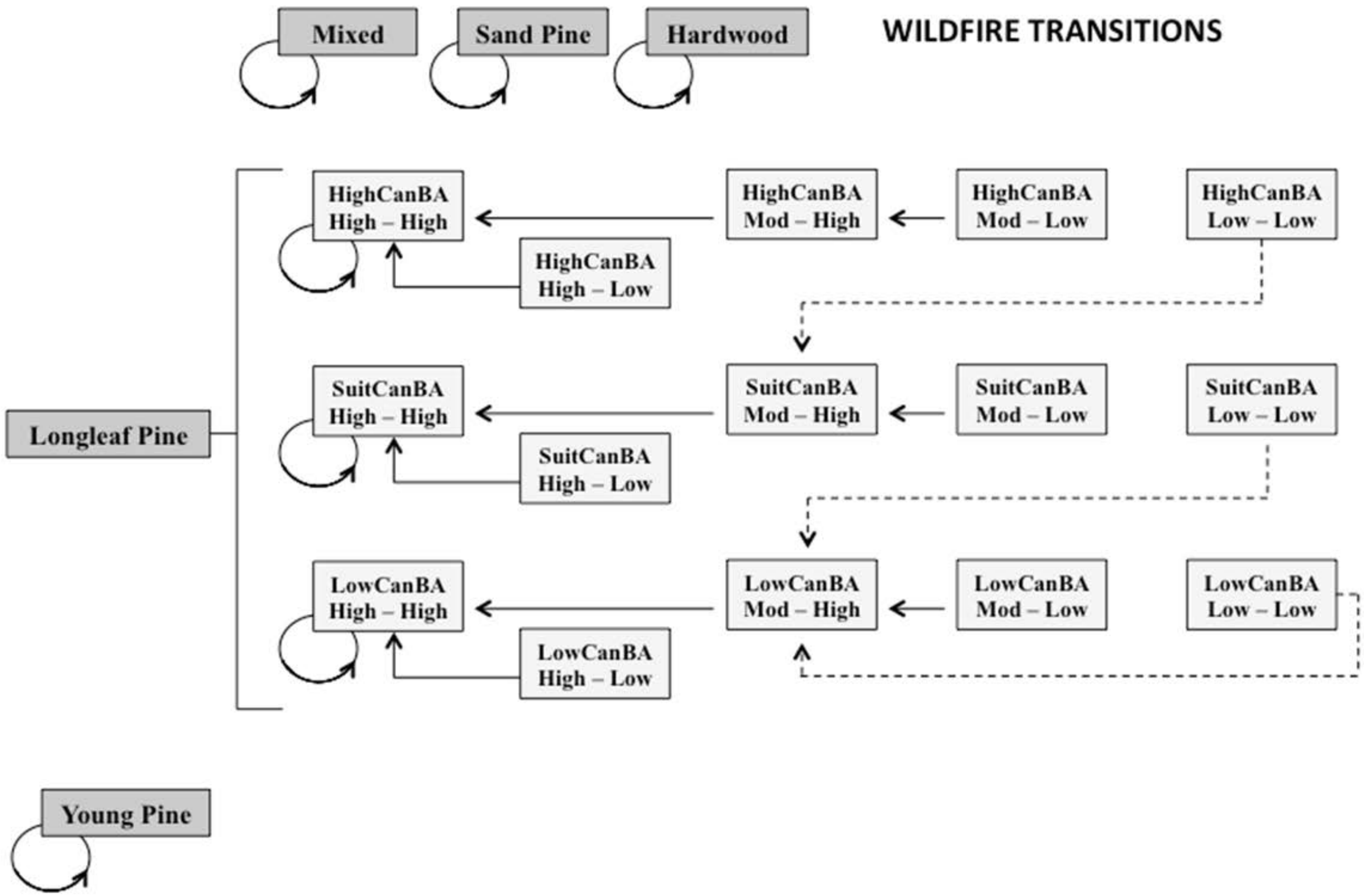


Figure D-1.5 Transition pathways for landcover states as a result of wildfires in the ST-SIM landscape model for Eglin AFB. Transitions for low intensity fires, which occur in states that have recently been burned and contain a thin layer of ground litter, are shown in solid lines. Transitions for high intensity fires, which occur in states with a history of fire suppression and contain a thick layer of ground litter, are shown in dashed lines. Transitions for longleaf pine states are the same for the ≥ 60 years old and 15-59 years old age classes. Finally, 1-acre landscape cells within all forested landcover states have an equal probability of experiencing a wildfire each year (2.2%).

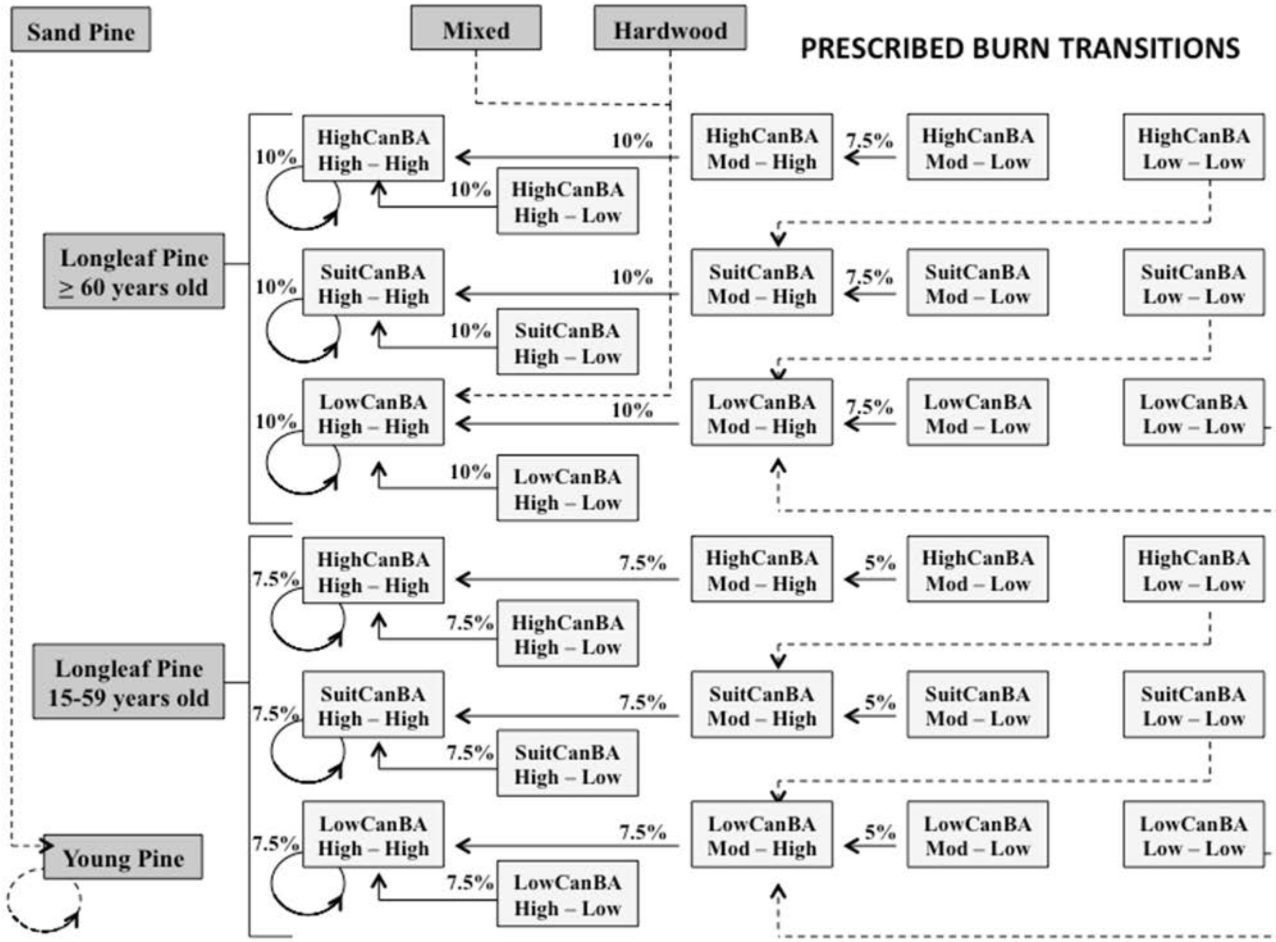


Figure D-1.6 Transition pathways for states as a result of prescribed burns in the ST-SIM landscape model for Eglin AFB. Probabilities given next to transition lines indicate the likelihood that landscape cells belonging to each state will experience a prescribed burn in a given time step relative to the other states. State transition pathways illustrated by dashed lines have a 0% probability of occurring in the baseline model. These landcover types are rarely burned on the actual Eglin landscape, and pathways were provided only to allow the user to test alternative management regimes.

In the ST-SIM model, as in the actual landscape at Eglin AFB, fires either occur as wildfires (i.e., occurring through lightning strikes, vandalism, or other means; Figure D-1.5) or as intentional prescribed burns set for management purposes (Figure D-1.6). Wildfires burn approximately 10,000 acres in this landscape each year, while prescribed fires burn approximately 104,000 acres each year (Eglin AFB Fire Management Data, Hiers, pers. comm.). Thus, in the ST-SIM model, we assume that longleaf pine states have annual wildfire and prescribed burn probabilities of 2.2%. For prescribed burns, probabilities shown in Figure D-1.6 were used to indicate the relative probability that each landscape state would be burned compared to another, and we governed the area of the landscape that should experience prescribed burns through a management target. We also varied the size of fires in the model according to actual fire behavior at Eglin; a single wildfire or prescribed burn on the base can consume from less than 5 acres to more than 4,000 acres at a time. Most individual (i.e., contiguous) wildfires impact less than 5 acres (mean: 95 acres, median: 5 acres, St.D: 355), and most individual prescribed burns impact between 100 and 500 acres (mean: 709 acres, median: 415 acres, St.D: 815; Eglin AFB Fire Management Data; Figure D-1.7).

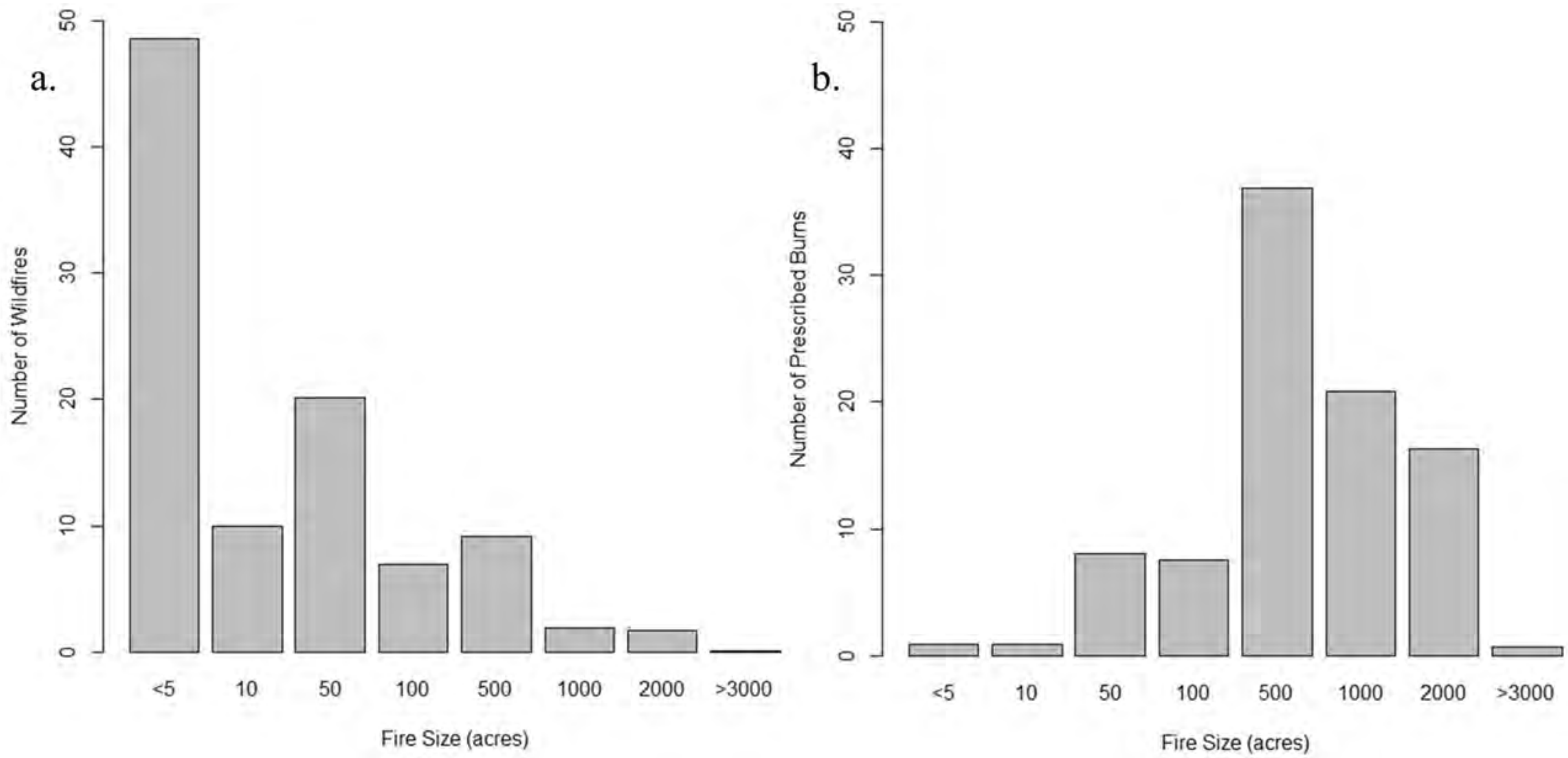
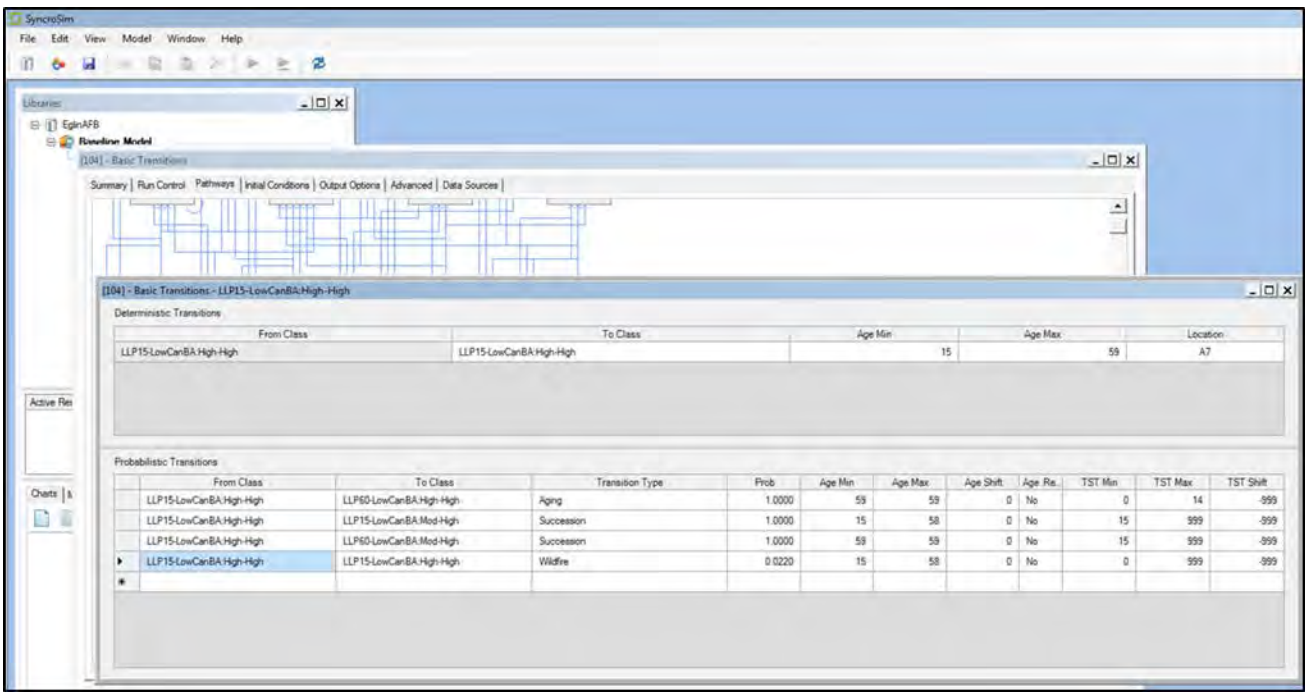


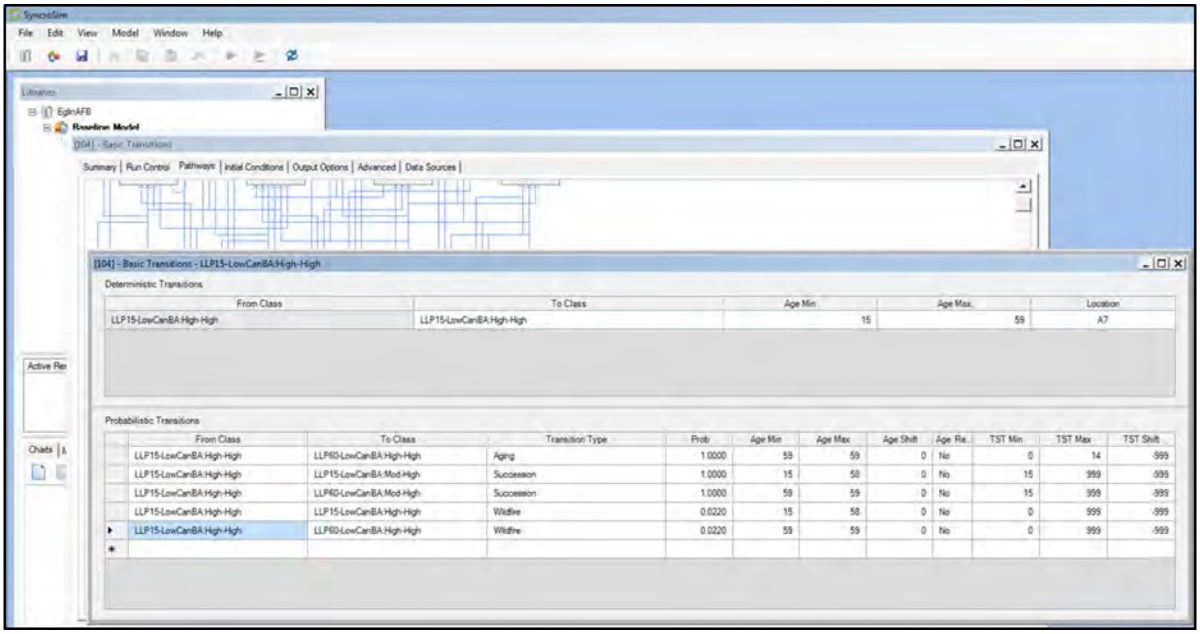
Figure D-1.7 Average annual frequency of fires in each size class for (a) wildfires and (b) prescribed burns at Eglin AFB (data from Eglin AFB Fire Management from 1998-2011). X-axis intervals encompass the range from the previous interval to the current interval (e.g., "10" on x-axis shows the number of fires from 6 to 10 acres in size, "50" shows the number of fires from 11 to 50 acres in size, etc).

Fire transitions are added in the same manner as the successional transitions; double-click on a gray state box under the “Pathways” tab in the main window for this scenario. The “Basic Transitions” window for this specific state class will open. As an example, open the “Basic Transitions” window for LLP15-LowCanBA:High-High. Under “Probabilistic Transitions” you will see the transition(s) for Succession and Aging (if applicable) that were added in the previous sub-sections. Re-add the columns for “Ages” and “TST” if those columns have disappeared (right-click in the top left cell of the table under “Probabilistic Transitions”; see previous sub-section). In the row under the last transition added, select “LLP15-LowCanBA:High-High” under the column “From Class”, the same state under the column “To Class”, and “Wildfire” under “Transition Type”. Under “Prob”, input “0.022”. Select the minimum and maximum ages that a stand/cell must be within to exist in this stage class under “Age Min” and “Age Max” (in this case, “15” and “58”), and input “0” and “No” for “Age Shift” and “Age Reset”. Finally, input “0”, “999”, and “-999” for “TST Min”, “TST Max”, and “TST Shift”, respectively. These parameters indicate that, for this state with a recent fire history, a stand or landscape cell has a 2.2% chance of experiencing a wildfire and that the landscape cell’s recent fire history will not affect its probability of experiencing another fire. If a wildfire does occur, then the fire will maintain the cell in its current state, and longleaf pines will continue to age from their present condition (i.e., the fire does not clear the stand and revert trees to year 0).

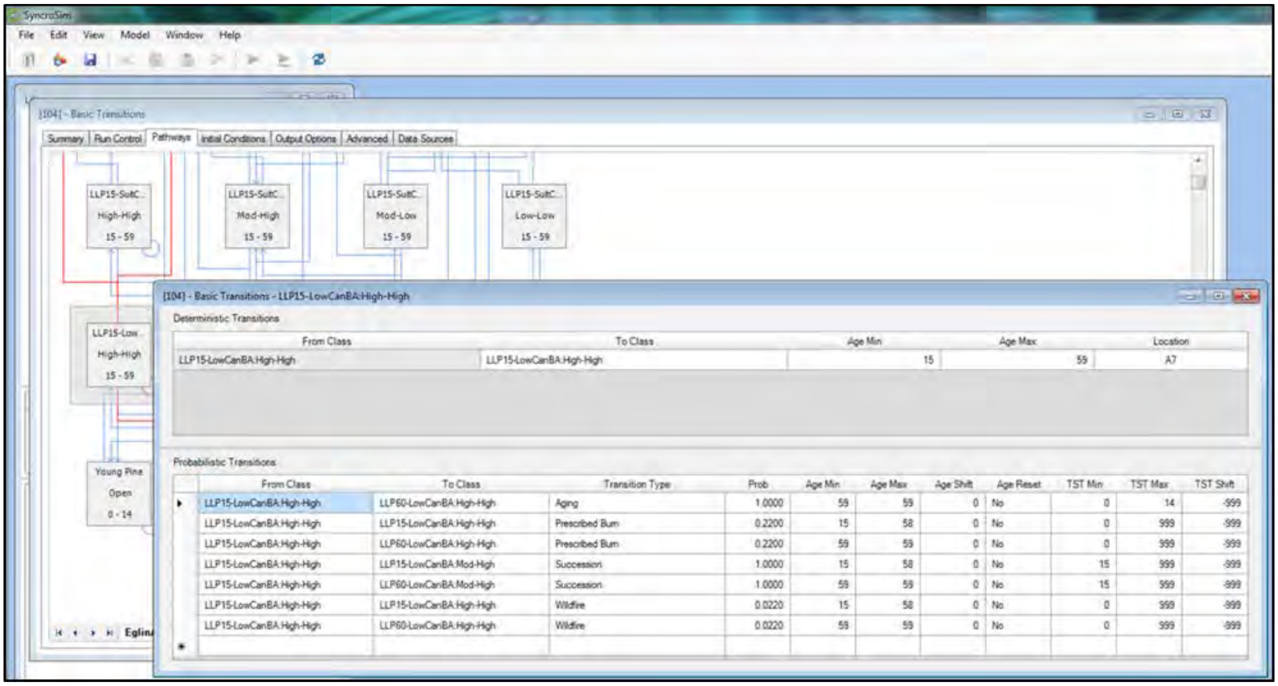


In addition, the cells within the states for Longleaf Pine 15-59 years old (LLP15) could also age up to states for Longleaf Pine ≥ 60 years old (LLP60) while experiencing a fire in the same time step. As in the input for the Succession transition, you will also need to add a second Wildfire transition for all LLP15 state classes. Continuing with the example for the state LLP15-LowCanBA:High-High, right click on that state’s gray state box in the “Pathways” tab. In the row under the last transition added, select “LLP15-LowCanBA:High-High” under the column “From Class”, the appropriate LLP60 state (see Figure D-1.5, Table D-1.8) under the column “To Class” (here, “LLP60-LowCanBA:High-High”), and “Wildfire” under “Transition Type”.

Under “Prob”, input “0.022”. Select “59” for both “Age Min” and “Age Max”, and input “0” and “No” for “Age Shift” and “Age Reset”. Finally, input “0”, “999”, and “-999” for “TST Min”, “TST Max”, and “TST Shift”, respectively.



In the next line of this window, add all of the same values under the appropriate columns that were added for Wildfire, with the exception of inputting “Prescribed Burn” under “Transition Type” and the specific probability that the state will experience a prescribed burn (given in Figure D-1.6) under “Prob”. In this example, this parameterization indicates that a prescribed burn in a landscape cell of this particular state (LLP15-LowCanBA:High-High) can occur with a 7.5% probability and would maintain the cell in its current state. A prescribed burn would not affect the age of the stand/landscape cell, and the probability of a prescribed burn occurring is not dependent on the landscape cell’s recent fire history. A second Prescribed Burn transition should also be added for all LLP15 states where the “Age Min” and “Age Max” are both “59”.



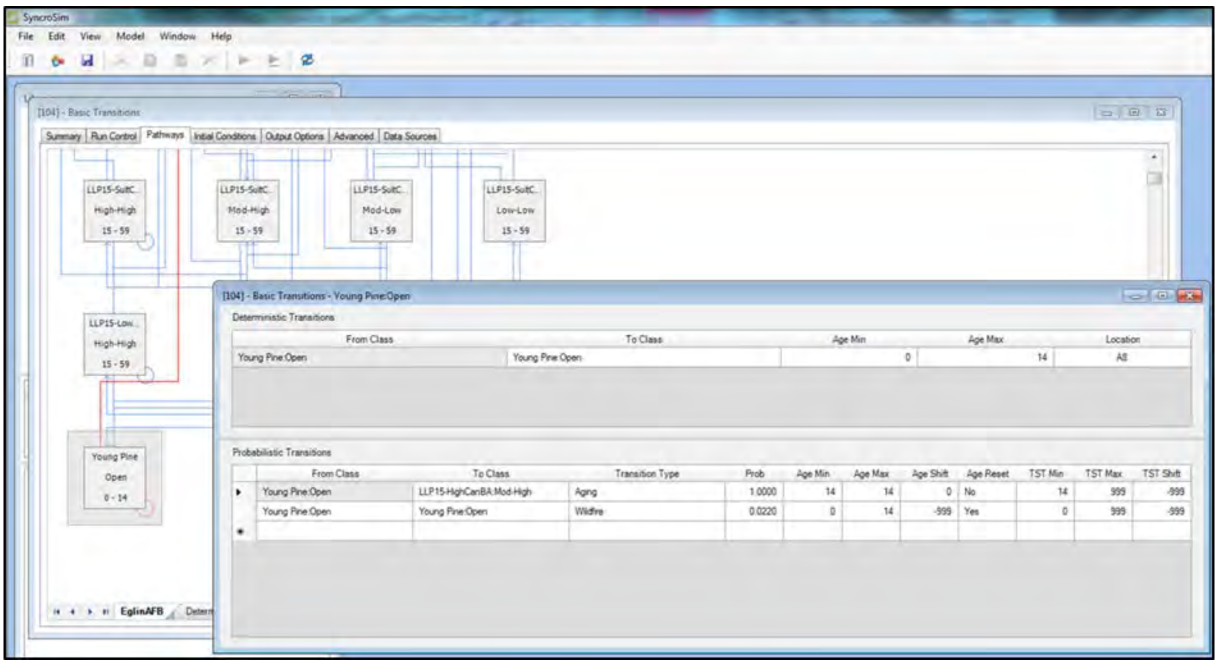
This process should be repeated for all longleaf pine states. Parameters for "Transition Type", "Age Shift", "Age Reset", "TST Min", "TST Max", and "TST Shift" will be the same as those described in the previous two paragraphs regardless of the original state class. The values for "Age Min" and "Age Max" will always correspond to the "Age Min" and "Age Max" of the state class, as given under the "Deterministic Transitions" table of the "Basic Transitions" window for the focal state class (Open = 0-14; LLP15 = 15-58 or 59-59, LLP60 = 60-999). In the case of fire transitions added to the LLP15 states to account for both fire and aging, the "Age Min" and "Age Max" should both be "59". The state selected under "To Class" will be the same for both the Wildfire and the Prescribed Burn transitions and will vary depending on the Structural Stage of the original state class according to Table D-1.9, Figure D-1.5, and Figure D-1.6.

Table D-1.9 Changes in longleaf pine landscape states following Wildfire and Prescribed Burn transitions (shifts in state class will be the same regardless of age category).

Original State ("From Class")	**Resulting State ("To Class")**	**Burn Intensity[1]**
HighCanBA/SuitCanBA/LowCanBA: High-High	HighCanBA/SuitCanBA/LowCanBA: High-High	Low
HighCanBA/SuitCanBA/LowCanBA: High-Low	HighCanBA/SuitCanBA/LowCanBA: High-High	Low
HighCanBA/SuitCanBA/LowCanBA: Mod-High	HighCanBA/SuitCanBA/LowCanBA: High-High	Low
HighCanBA/SuitCanBA/LowCanBA: Mod-Low	HighCanBA/SuitCanBA/LowCanBA: Mod-High	Low
HighCanBA:Low-Low	SuitCanBA:Mod-High	High
SuitCanBA:Low-Low	LowCanBA:Mod-High	High
LowCanBA:Low-Low	LowCanBA:Mod-High	High

[1]Fires that occur at low intensity do not impact the canopy BA while those that occur at high intensity thin the canopy BA.

The Young Pine state can also experience the Wildfire transition. Parameterization for this state class and transition includes the following: “Young Pine” for “From Class”, “Young Pine” under “To Class”, “Wildfire” under “Transition Type”, “0.022” under “Prob”, “0” for “Age Min”, “14” for “Age Max”, “-999” for “Age Shift”, “Yes” for “Age Reset”, “0” for “TST Min”, “999” for “TST Max”, and “-999” for “TST Shift”. These parameters indicate that a landscape cell in the Young Pine state class, regardless of the cell’s age, has a 2.2% chance of experiencing a wildfire. This probability is not impacted by the cell’s recent fire history, and, when the fire occurs, the age of the cell will revert back to 0. Like the LLP15-LowCanBA:Low-Low state, the Young state does not require a Wildfire and Aging transition for 14 year old stands because the age of the stand reverts back to 0 when fire occurs in any landscape cell in this state.

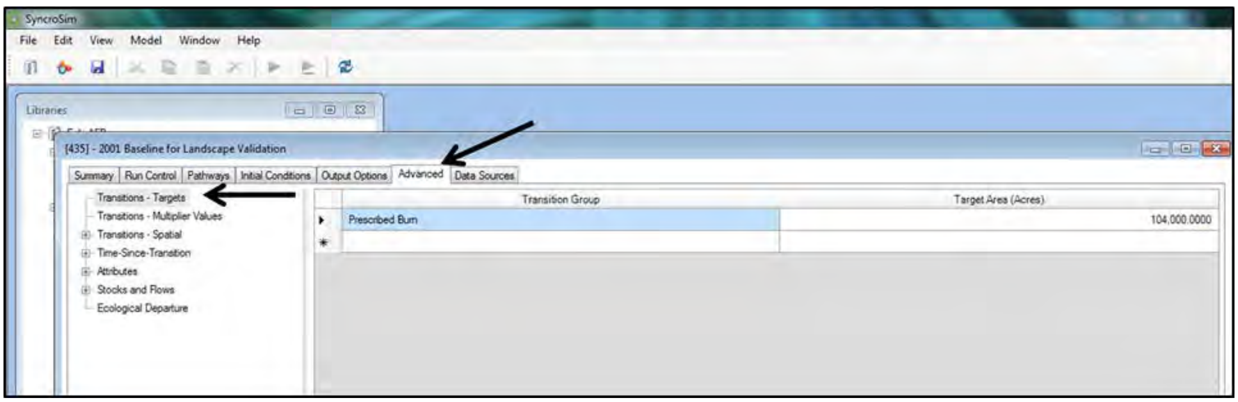


We also added a transition for Prescribed Burn for the Young Pine landscape state; however, because Young Pine stands are rarely burned intentionally, we indicated that the probability that this landscape state would experience a Prescribed Burn was 0%. Add this transition accordingly as described for the Longleaf Pine states.

Finally, the Mixed, Sand Pine, and Hardwood landcover states can also experience the Wildfire Transition with probability 2.2%. When a Wildfire occurs in a landscape cell characterized by these landscape states, the cell’s landcover state and age will remain the same (Figure D-1.5). We also added Prescribed Burn transitions for these states so that the user could explore alternative management regimes for these states; however, in the baseline model, we indicated that these landscape states had a 0% probability of experiencing a Prescribed Burn (Figure D-1.6). Add these Wildfire and Prescribed Burn transitions accordingly as described for the Longleaf Pine states.

For all other state classes (i.e., Bare Land and Water), we assumed that fires could not occur. Thus, for these states, we did add parameters for Wildfire or Prescribed Burn transitions.

Thus far, we have added both fire transitions as having a *probability* of occurring. However, in highly managed landscapes like Eglin AFB, base managers may have specific targets for management, which can be parameterized in the ST-SIM model. In the case of prescribed burns, Eglin managers burn approximately 104,000 acres each year (Eglin AFB Fire Management Data, Hiers, pers. comm.). In the "Basic Transition" window, click on the "Advanced" tab, and select "Transitions-Targets" on the menu along the left-hand side of the screen. In the table to the right, choose "Prescribed Burn" in the dropdown for "Transition Group", and add "104,000" under "Target Area (Acres)". This parameter also provides the user with an opportunity to explore the potential impacts of changing management targets. For example, a user could evaluate the amount of available RCW habitat present if the prescribed burn management target was reduced from 104,000 acres to 50,000 acres.

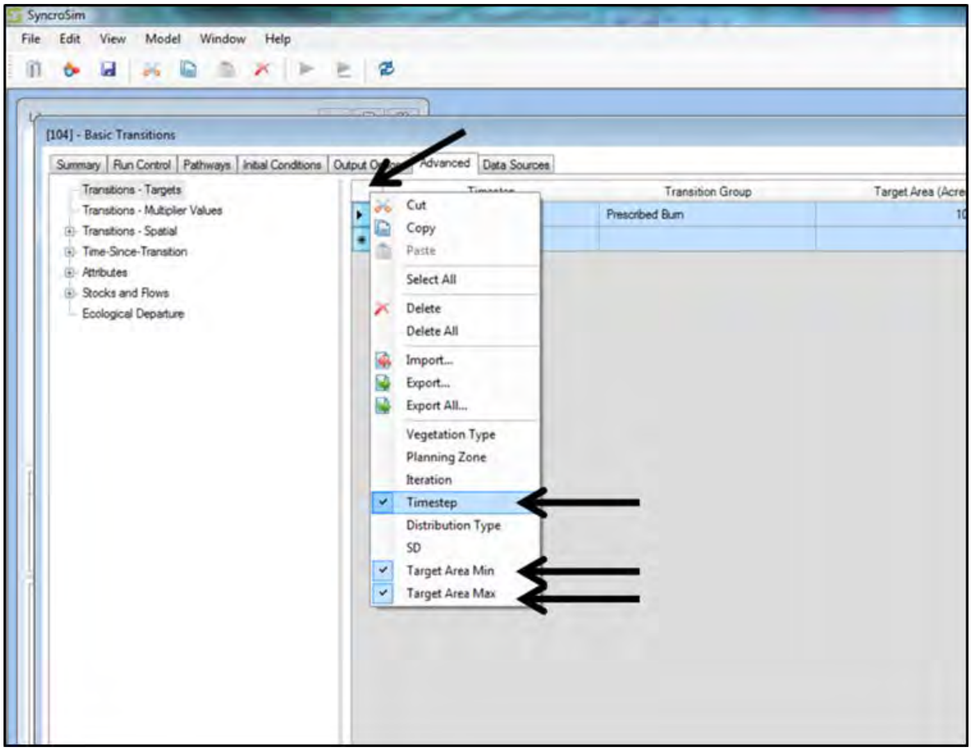


If this option is not enabled, each eligible landscape cell would have an independent, user-specified probability (probability given in Figure D-1.6) of experiencing a Prescribed Burn each time step. In addition, if one cell is affected by the Prescribed Burn transition, the probability of any other cell experiencing the Prescribed Burn transition would not change. As a result, there could be some simulation years where a prescribed burn does not occur in any cell and other years where a prescribed burn occurs in every eligible cell (although this would be unlikely, particularly in large landscapes). However, by setting a transition target, the user forces the model to simulate this transition in a user-specified number of landscape cells (here, the number of cells comprising 104,000 acres) each simulation year. The transition can still only occur in cells that are within the eligible landscape states, and the transition will preferentially occur in states with the highest probability of experiencing that transition (so it remains critical that the probabilistic Prescribed Burn transition is added for the Longleaf Pine states as described earlier in this section). If specific states are preferentially burned, then this can be added to the simulation by increasing the prescribed burn for those states relative to others.

In should be noted, however, that there is no guarantee that this transition target will be met each simulation year. For example, in the scenario developed in this manual, there may be years where there are fewer than 104,000 acres of longleaf pine on the landscape (although this is unlikely given our parameterization). If this happens, then the transition target cannot be met because there will not be enough landscape cells in the eligible landscape states.

The user can also specify that targets be used only for certain simulation years and/or that a target occurs within an area range (instead of a single target value). This can be done by right-

clicking on the cell in the top-left corner of the "Transition Targets" table; selecting "Time Step", "Target Area Min", and "Target Area Max"; and inputting the appropriate values in the table.



It is also important for the user to add a range of size distributions for the Wildfire and Prescribed Burn transitions (whether or not transition targets are used) that are associated with the sizes of actual fires on the landscape (Figure D-1.7). To add a distribution for fire sizes according to Figure D-1.7, click on the "Advanced Tab" in the "Basic Transitions" scenario window. Click the "+" sign next to "Transitions – Spatial" on the left side of this screen (if this menu is not already expanded). Then, click on "Size Distribution". In the first row of the table that appears, input "Wildfire" under "Transition Group", "5" under "Maximum Area", and "0.493" under "Relative Amount". This indicates that 49% of all wildfires that occur in a given simulation will affect between 0 and 5 acres of the landscape. Repeat this process for maximum areas up to 4,500 acres with size proportions according to Table D-1.10.

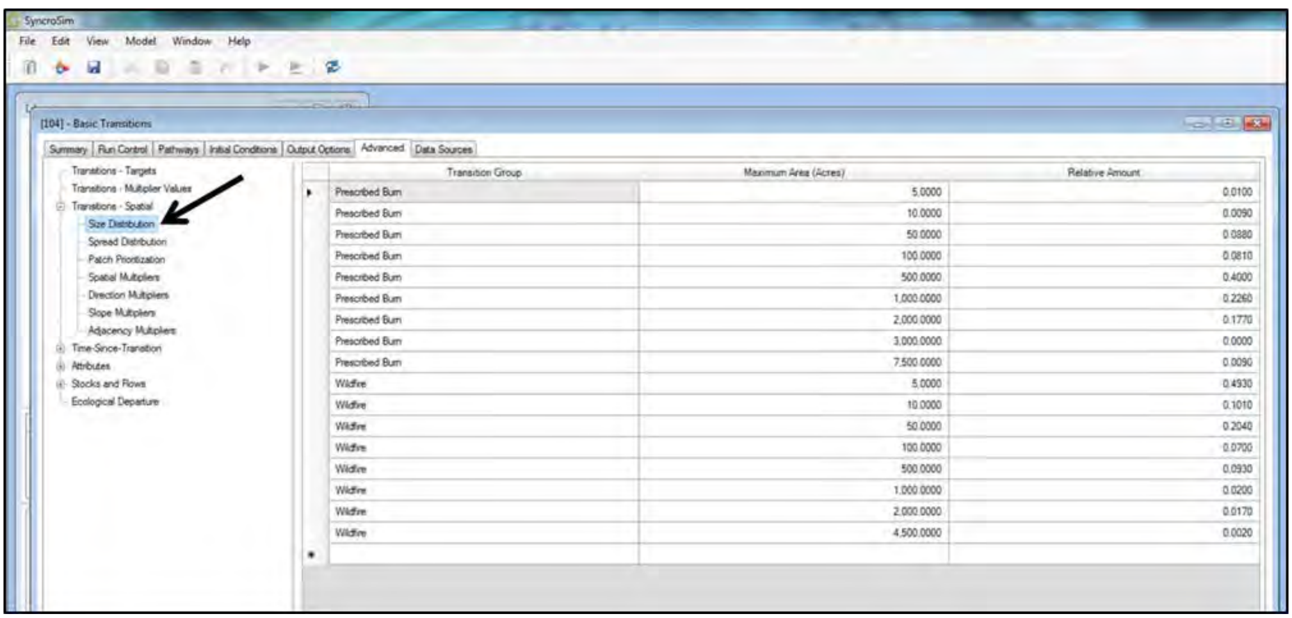
Table D-1.10 Fire size distributions for all wildfires that occur in a given ST-SIM simulation.

Maximum Area (Acres)	**Relative Amount**
5 (< 5)	0.493
10 (5 - 10)	0.101
50 (10 – 50)	0.204
100 (50 – 100)	0.070
500 (100 - 500)	0.093
1000 (500 – 1000)	0.020
2000 (1000 – 2000)	0.017
4500 (> 2000)	0.002

Repeat this process to add a size distribution for the Prescribed Burn transition. In the first empty row of this table (after the last wildfire entry), input “Prescribed Burn” under “Transition Group”, “5” under “Maximum Area”, and “0.010” under “Relative Amount”. This indicates that 1% of all prescribed burns that occur in a given simulation will affect between 0 and 5 acres of the landscape. Repeat this process for maximum areas up to 7,500 acres with size proportions according to Table D-1.11.

Table D-1.11 Fire size distributions for all prescribed burns that occur in a given ST-SIM simulation.

Maximum Area (Acres)	Relative Amount
5 (< 5)	0.010
10 (5 - 10)	0.009
50 (10 – 50)	0.088
100 (50 – 100)	0.081
500 (100 - 500)	0.400
1000 (500 – 1000)	0.226
2000 (1000 – 2000)	0.177
3000 (2000 – 3000)	0.000
7500 (> 3000)	0.009

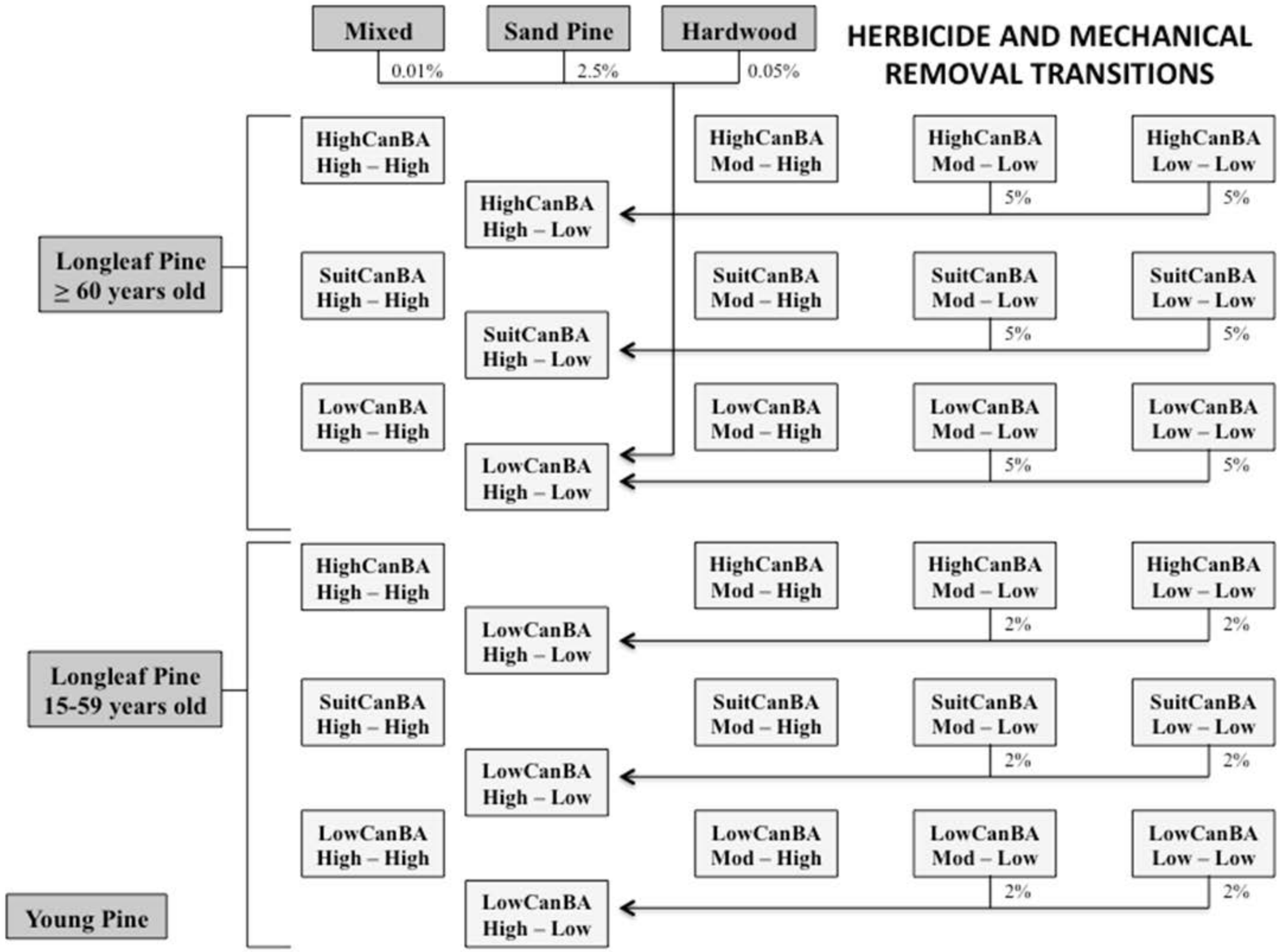


4.3.4 Herbicide Treatment

In addition to fire, a large-scale study of restoration techniques at Eglin AFB also showed that the use of herbicides, specifically the ULW®-form of hexazinone, was extremely effective in reducing the hardwood midstory (Provencher et al. 2001a; Provencher et al. 2001b). Given the effectiveness of the use of herbicide in restoring longleaf pine communities, we included herbicide as a potential management option in the ST-SIM landscape model. In this model, herbicide application does not impact canopy BA but does improve RCW habitat suitability by

increasing midstory suitability (Figure D-1.8). In addition, only landscape states with moderate to low midstory suitability and low understory cover are eligible for herbicide application.

At Eglin, 1,000 acres are treated with herbicides each year (Hiers, pers. comm. 2010). We also provided each landscape state with a relative probability that it would be treated with herbicide according to Hiers (pers. comm. 2010; Figure D-1.8) Users of the ST-SIM or linked ST-SIM -RCW population model can further test the impact of herbicide application on habitat and RCW habitat suitability by increasing or decreasing landscape-specific probabilities or the transition target.

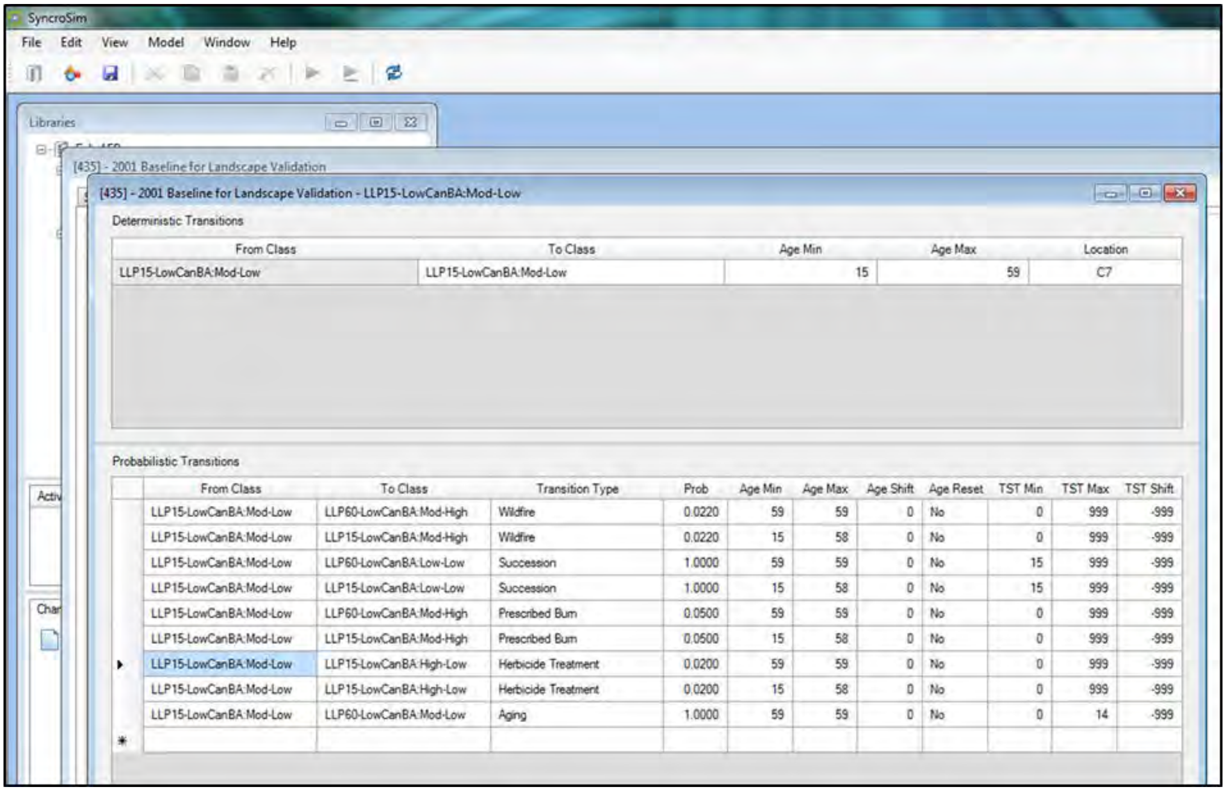


[1]Landscape cells in the Sand Pine state have a 0% probability of experiencing an herbicide transition but a 2.5% probability of experiencing a mechanical removal transition.

Figure D-1.8 Transition pathways for landcover states following herbicide and mechanical removal treatments in the ST-SIM baseline landscape model for Eglin AFB. Probabilities given next to transition lines indicate the likelihood that landscape cells belonging to each state will experience a management treatment in a given time step relative to the other states (probabilities equivalent for herbicide and mechanical midstory removal[1]).

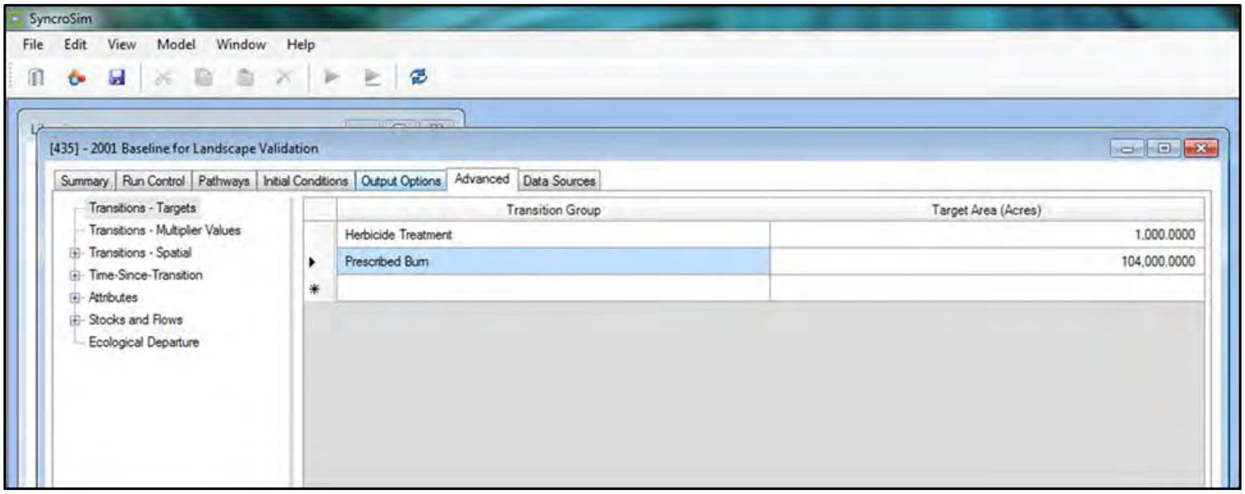
Transitions for herbicide treatment are added in the same manner as described in the previous sub-section (*4.3.3 Fire*). In this model, we assume that landscape states eligible for herbicide treatment must have Structural Stages that are characterized by moderate midstory suitability and low understory cover (Mod-Low) or by low midstory suitability and low understory cover (Low-Low). Double-click on any gray state class box for longleaf pine states meeting this condition for Structural Stage under the "Pathways" tab in the "Basic Transitions" scenario window. As an example, double-click on the state box for LLP15-LowCanBA:Mod-Low. Select "LLP15-LowCanBA:Mod-Low" for "From Class", "LLP15-LowCanBA:High-Low" for "To Class", and "Herbicide Treatment" for "Transition Type". Input "0.02" for "Prob", "15" for "Age Min", "58" for "Age Max", "0" for "Age Shift", "No" for "Age Reset", "0" for "TST Min", "999" for "TST Max", and "-999" for "TST Shift". These parameters indicate that a landscape cell in state LLP15-LowCanBA:Mod-Low has a 2% probability of being treated with herbicide. If it is treated, the Structural Stage for that cell will move to one characterized by high midstory suitability and low understory cover (High-Low) without the canopy being affected. The probability of treatment is not affected by the cell's disturbance history, and the ages of longleaf pines in the cell will not be impacted by treatment.

For the eligible LLP15 states, a second transition for Herbicide Treatment should also be added for cells/stands that are 59 years old to account for both Aging and Herbicide Treatment.



This process should be repeated for all longleaf states characterized by moderate midstory suitability and low understory cover (Mod-Low) or by low midstory suitability and low understory cover (Low-Low). Regardless of the state's original Structural Stage, herbicide treatment always changes the state to one characterized by high midstory suitability and low understory cover (High-Low; Figure D-1.8). Cover Type is never altered (Figure D-1.8), and "Age Min" and "Age Max" should correspond to the original state's age range (i.e., 15-58 or 59-59 for LLP15 and 60-999 for LLP60 states). All other inputs are the same as those described in the previous paragraph.

Finally, as discussed for prescribed burns in section *4.3.3 Fire*, the user can set a transition target for the Herbicide Treatment transition. Eglin managers treat approximately 1,000 acres with herbicides (and spring burns) each year (Eglin AFB Fire Management Data, Hiers, pers. comm.). In the ST-SIM model, the user can specify this management target in the "Basic Transitions" window by clicking on the "Advanced" tab and selecting "Transitions-Targets" on the menu along the left-hand side of the screen. In the table to the right, under the entry for "Prescribed Burn", select in the dropdown for "Herbicide Treatment" under the "Transition Group", and add "1,000" under "Target Area (Acres)".



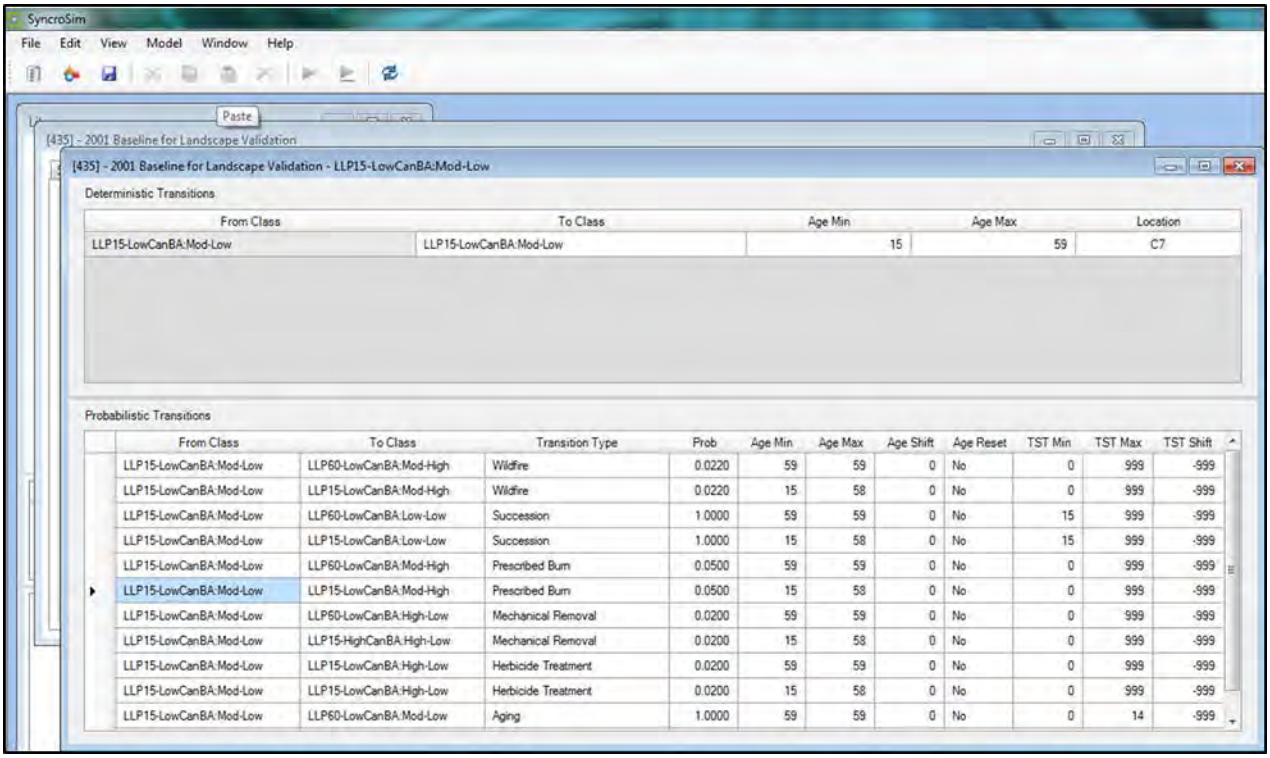
4.3.5 Mechanical Removal

Mechanical chainsaw felling and girdling of hardwood species in the midstory is also a commonly used restoration technique in the longleaf pine ecosystem at Eglin AFB, and we included this technique as a possible management option in the ST-SIM landscape model. Like the herbicide application, mechanical removal does not impact canopy BA but does increase midstory suitability (and ultimately RCW habitat suitability) for eligible landscape states. Only landcover states with moderate to low midstory suitability and low understory cover are eligible for mechanical removal treatment.

At Eglin, 7,000 acres are cleared by mechanical removal each year (Hiers, pers. comm.), and the probability that a landscape cell (or stand) will be treated with mechanical removal is dependent on its landscape state (Figure D-1.8). Again, this target and these state-specific probabilities serve as baseline conditions in our landscape model, but users can further test the impact of mechanical removal on habitat and RCW habitat suitability by increasing or decreasing these parameters.

Transitions for Mechanical Removal are added in the same manner as described in the previous sub-section (*4.3.4 Herbicide Treatment*). Landscape states eligible for mechanical removal must have Structural Stages characterized by moderate midstory suitability and low understory cover (Mod-Low) or by low midstory suitability and low understory cover (Low-Low). Double-click on any gray state class box for longleaf pine states meeting this condition for Structural Stage under the "Pathways" tab in the "Basic Transitions" scenario window. As an example, double-click on the state box for LLP15-LowCanBA:Mod-Low. Select "LLP15-LowCanBA:Mod-Low" for "From Class", "LLP15-LowCanBA:High-Low" for "To Class", and "Mechanical Removal" for "Transition Type". Input "0.02" for "Prob", "15" for "Age Min", "58" for "Age Max", "0" for "Age Shift", "No" for "Age Reset", "0" for "TST Min", "999" for "TST Max", and "-999" for "TST Shift". These parameters indicate that a landscape cell in state LLP15-LowCanBA:Mod-Low has a 2% probability of being treated with mechanical removal techniques followed by a prescribed burn. If it is treated, the Structural Stage for that cell will move to one characterized by high midstory suitability and low understory cover (High-Low) without the canopy being affected. The probability of treatment is not affected by the cell's disturbance history, and the ages of longleaf pines in the cell will not be impacted by treatment.

For the eligible LLP15 states, a second transition for Mechanical Removal should also be added for cells/stands that are 59 years old to account for both Aging and Mechanical Removal.

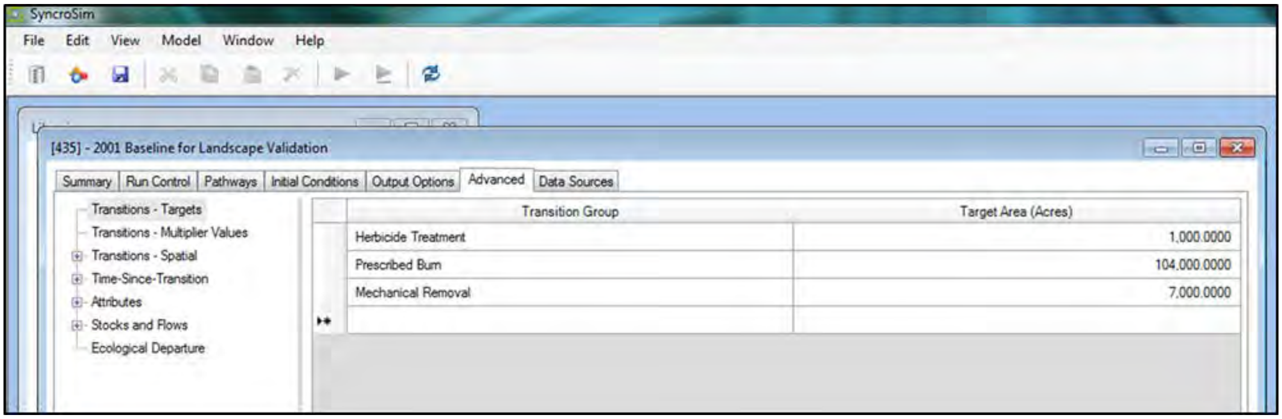


From Class	To Class	Age Min	Age Max	Location
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:Mod-Low	15	59	C7

From Class	To Class	Transition Type	Prob	Age Min	Age Max	Age Shift	Age Reset	TST Min	TST Max	TST Shift
LLP15-LowCanBA:Mod-Low	LLP60-LowCanBA:Mod-High	Wildfire	0.0220	59	59	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:Mod-High	Wildfire	0.0220	15	58	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP60-LowCanBA:Low-Low	Succession	1.0000	59	59	0	No	15	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:Low-Low	Succession	1.0000	15	58	0	No	15	999	-999
LLP15-LowCanBA:Mod-Low	LLP60-LowCanBA:Mod-High	Prescribed Burn	0.0500	59	59	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:Mod-High	Prescribed Burn	0.0500	15	58	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP60-LowCanBA:High-Low	Mechanical Removal	0.0200	59	59	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-HighCanBA:High-Low	Mechanical Removal	0.0200	15	58	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:High-Low	Herbicide Treatment	0.0200	59	59	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP15-LowCanBA:High-Low	Herbicide Treatment	0.0200	15	58	0	No	0	999	-999
LLP15-LowCanBA:Mod-Low	LLP60-LowCanBA:Mod-Low	Aging	1.0000	59	59	0	No	0	14	-999

This process should be repeated for all longleaf states characterized by moderate midstory suitability and low understory cover (Mod-Low) or by low midstory suitability and low understory cover (Low-Low). Regardless of the state's original Structural Stage, Mechanical Removal always changes the state to one characterized by high midstory suitability and low understory cover (High-Low; Figure D-1.8). Cover Type is never altered (Figure D-1.8), and "Age Min" and "Age Max" should correspond to the original state's age range (i.e., 15-58 or 59-59 for LLP15 and 60-999 for LLP60 states). All other inputs are the same as those described in the previous paragraph.

Finally, to add the current management target for Mechanical Removal on Eglin AFB, go to the "Advanced" tab in the "Basic Transitions" window, and select "Transitions-Targets" on the menu along the left-hand side of the screen. In the table to the right, add an entry for "Mechanical Removal" under the "Transition Group", and add "7,000" under "Target Area (Acres)".



4.4 General Review of States and Transitions in the Basic Scenario

In summary, the ST-SIM model for the "Basic Transitions" scenario for Eglin AFB should include the states and transitions as shown in Table D-1.12.

Table D-1.12. States and their associated transitions contained in the "Basic Transitions" scenario for Eglin AFB in the ST-Sim model.

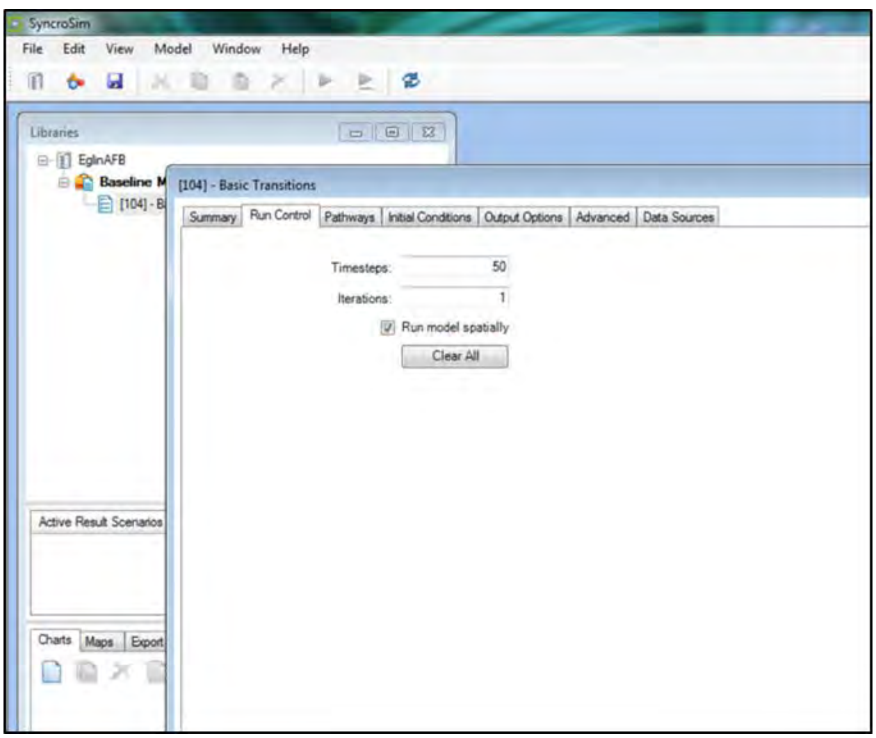
State	Succession	Aging	Prescribed Burn	Wildfire	Herbicide	Mechanical Removal	Total
Bare Land:Open	0	0	0	0	0	0	0
Developed:Open	0	0	0	0	0	0	0
Hardwood:Closed	0	0	1	1	1	1	4
Sand Pine:Closed	0	0	1	1	1	1	4
Young Pine:Open	0	1	1	1	0	0	3
Water:Open	0	0	0	0	0	0	0
Mixed:Closed	0	0	1	1	1	1	4
LLP15-HighCanBA:High-High	2	1	2	2	0	0	7
LLP15-HighCanBA:High-Low	2	1	2	2	0	0	7
LLP15-HighCanBA:Mod-High	2	1	2	2	0	0	7
LLP15-HighCanBA:Mod-Low	2	1	2	2	2	2	11
LLP15-HighCanBA:Low-Low	0	1	2	2	2	2	9
LLP15-SuitCanBA:High-High	2	1	2	2	0	0	7
LLP15-SuitCanBA:High-Low	2	1	2	2	0	0	7
LLP15-SuitCanBA:Mod-High	2	1	2	2	0	0	7
LLP15-SuitCanBA:Mod-Low	2	1	2	2	2	2	11
LLP15-SuitCanBA:Low-Low	0	1	2	2	2	2	9
LLP15-LowCanBA:High-High	2	1	2	2	0	0	7
LLP15-LowCanBA:High-Low	2	1	2	2	0	0	7
LLP15-LowCanBA:Mod-High	2	1	2	2	0	0	7
LLP15-LowCanBA:Mod-Low	2	1	2	2	2	2	11
LLP15-LowCanBA:Low-Low	0	1	2	2	2	2	9
LLP60-HighCanBA:High-High	1	0	1	1	0	0	3
LLP60-HighCanBA:High-Low	1	0	1	1	0	0	3
LLP60-HighCanBA:Mod-High	1	0	1	1	0	0	3
LLP60-HighCanBA:Mod-Low	1	0	1	1	1	1	5
LLP60-HighCanBA:Low-Low	1	0	1	1	1	1	5
LLP60-SuitCanBA:High-High	1	0	1	1	0	0	3
LLP60-SuitCanBA:High-Low	1	0	1	1	0	0	3
LLP60-SuitCanBA:Mod-High	1	0	1	1	0	0	3

LLP60-SuitCanBA:Mod-Low	1	0	1	1	1	1	5
LLP60-SuitCanBA:Low-Low	0	0	1	1	1	1	4
LLP60-LowCanBA:High-High	1	0	1	1	0	0	3
LLP60-LowCanBA:High-Low	1	0	1	1	0	0	3
LLP60-LowCanBA:Mod-High	1	0	1	1	0	0	3
LLP60-LowCanBA:Mod-Low	1	0	1	1	1	1	5
LLP60-LowCanBA:Low-Low	0	0	1	1	1	1	4

4.5 Simulation Controls and Initial Conditions

4.5.1 Run controls

Before running an ST-SIM model, parameters for the simulation characteristics and initial conditions must be selected. Click on the tab “Run Control” in the “Basic Transitions” scenario window. There, input the number of times steps, the number of iterations, and whether the model should be run spatially or not. The length of the time step and the number of time steps will vary depending on the scenario. As an example, we will simulate the model for 50 years assuming that one time step equals a single year. In addition, because this is a stochastic simulation of landscape dynamics, each iteration could result in a different distribution of landscape states. If you want to create an averaged distribution of landscape states, run the model for multiple iterations by adding a number > 1 next to “Iterations:” in this window. For example, if you select “10” here, ST-SIM will simulate the model from year 0 to year 50, repeating this process 10 times. Finally, the model can be run spatially by adding a check next to “Run model spatially” in this window. In this case, the model will use maps of the study area to determine the areas of the landscape states and their distributions (described in next paragraph), and it will output predictive maps as the simulation progresses. If this box is not checked, the user must indicate the percentage of the total landscape that is comprised of each landscape state (described in next paragraph). Accordingly, the model will not be spatially explicit, and maps will not be output at the end of the simulation. Instead, ST-SIM will indicate a predictive percentage of the total landscape that is comprised of each landscape state at the end of the simulation.



4.5.2 Initial landscape conditions

The areas for each landscape state and their distributions can be added by selecting the tab “Initial Conditions” in the “Basic Transitions” scenario window. Here, either a spatially explicit or a non-spatially explicit description of what the landscape looks like at the start (t = 0) of the simulation must be supplied.

If the simulation will be run non-spatially (the box in the previous screen was left unchecked), click on “Non-Spatial” to the left of this window. In this new window, indicate the total size of the landscape (in acres) and the number of simulation cells associated with the landscape in the corresponding input boxes. In the map we created for the distribution of all landscape states (section *7.1.1 State class map*), the landscape covered a total area of 458,229 acres and was composed of 458,229 cells (cell size: 1 acre).

Then, in the table associated with this window, add a row for each landscape state (section *4.1 Landscape States*) in the column “State Class”, select “EglinAFB” for every entry in the column “Vegetation Type”, and indicate the proportion of the total landscape comprised of each landscape state in the column “Relative Amount”. The values in the “Relative Amount” column should sum to 1. The relative amounts shown in the example screenshot below correspond to Eglin AFB in the year 2010 (Table D-1.13; section *8.1 State class map*).

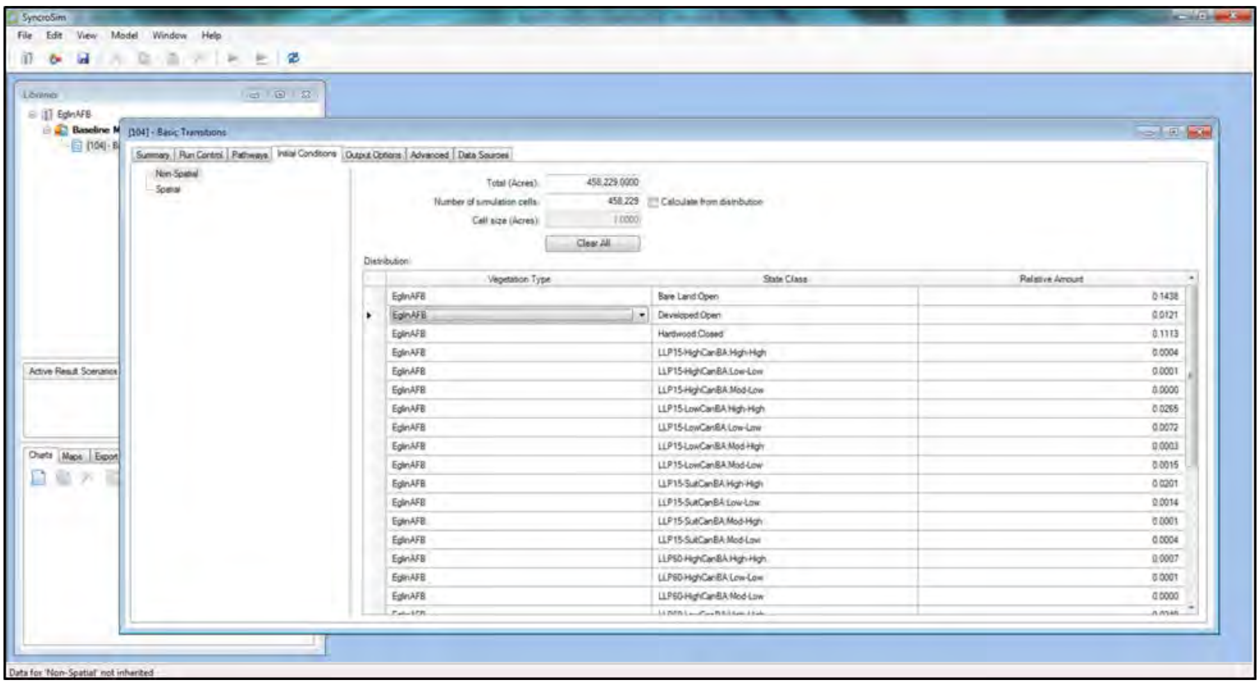
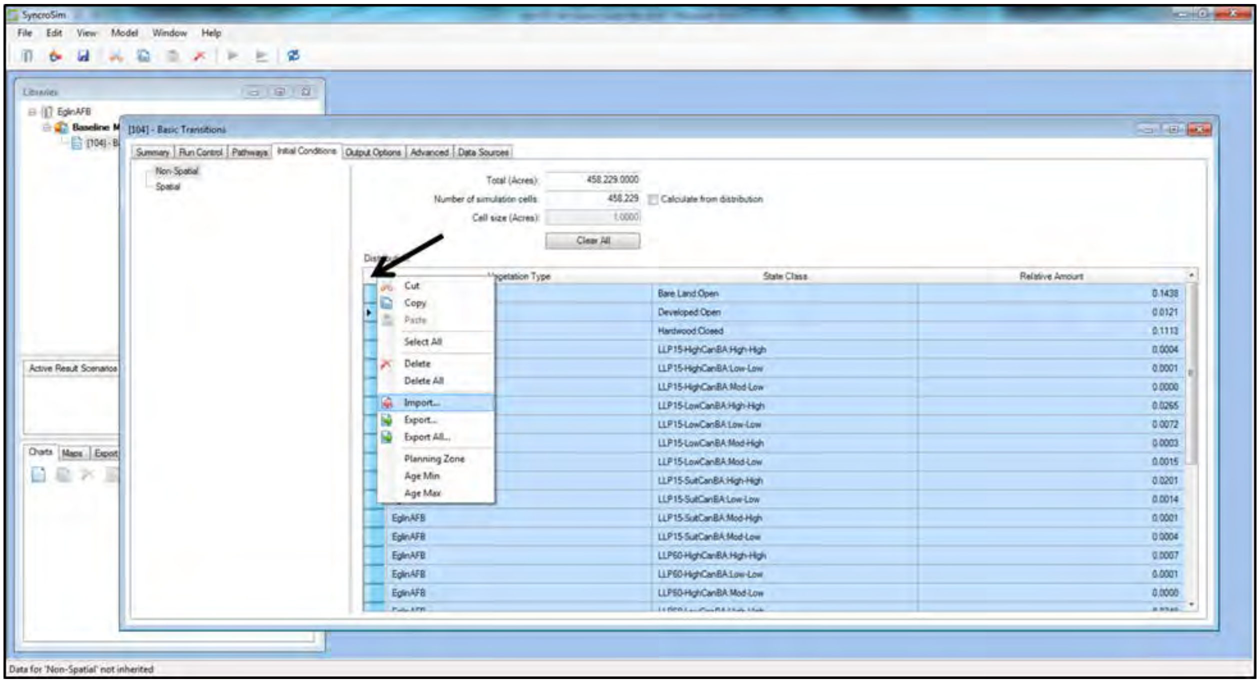


Table D-1.13 Relative proportions of each ST-SIM landscape state at Eglin AFB in the year 2010. This information can be used to initialize a non-spatially explicit simulation the ST-SIM landscape model for this military installation.

State	Relative Proportion of Landscape
Bare Land:Open	0.14
Developed:Open	0.01
Hardwood:Closed	0.11
Sand Pine:Closed	0.16
Young Pine:Open	0.03
Water:Open	0.00
Mixed:Closed	0.26
LLP15-HighCanBA:High-High	0.00
LLP15-HighCanBA:High-Low	0.00
LLP15-HighCanBA:Mod-High	0.00
LLP15-HighCanBA:Mod-Low	0.00
LLP15-HighCanBA:Low-Low	0.00
LLP15-SuitCanBA:High-High	0.02
LLP15-SuitCanBA:High-Low	0.00
LLP15-SuitCanBA:Mod-High	0.00
LLP15-SuitCanBA:Mod-Low	0.00
LLP15-SuitCanBA:Low-Low	0.00
LLP15-LowCanBA:High-High	0.03
LLP15-LowCanBA:High-Low	0.00
LLP15-LowCanBA:Mod-High	0.00
LLP15-LowCanBA:Mod-Low	0.00
LLP15-LowCanBA:Low-Low	0.01
LLP60-HighCanBA:High-High	0.00
LLP60-HighCanBA:High-Low	0.00
LLP60-HighCanBA:Mod-High	0.00
LLP60-HighCanBA:Mod-Low	0.00
LLP60-HighCanBA:Low-Low	0.00
LLP60-SuitCanBA:High-High	0.18
LLP60-SuitCanBA:High-Low	0.00
LLP60-SuitCanBA:Mod-High	0.00
LLP60-SuitCanBA:Mod-Low	0.00
LLP60-SuitCanBA:Low-Low	0.00
LLP60-LowCanBA:High-High	0.02
LLP60-LowCanBA:High-Low	0.00
LLP60-LowCanBA:Mod-High	0.00
LLP60-LowCanBA:Mod-Low	0.00
LLP60-LowCanBA:Low-Low	0.01
Total	1.00

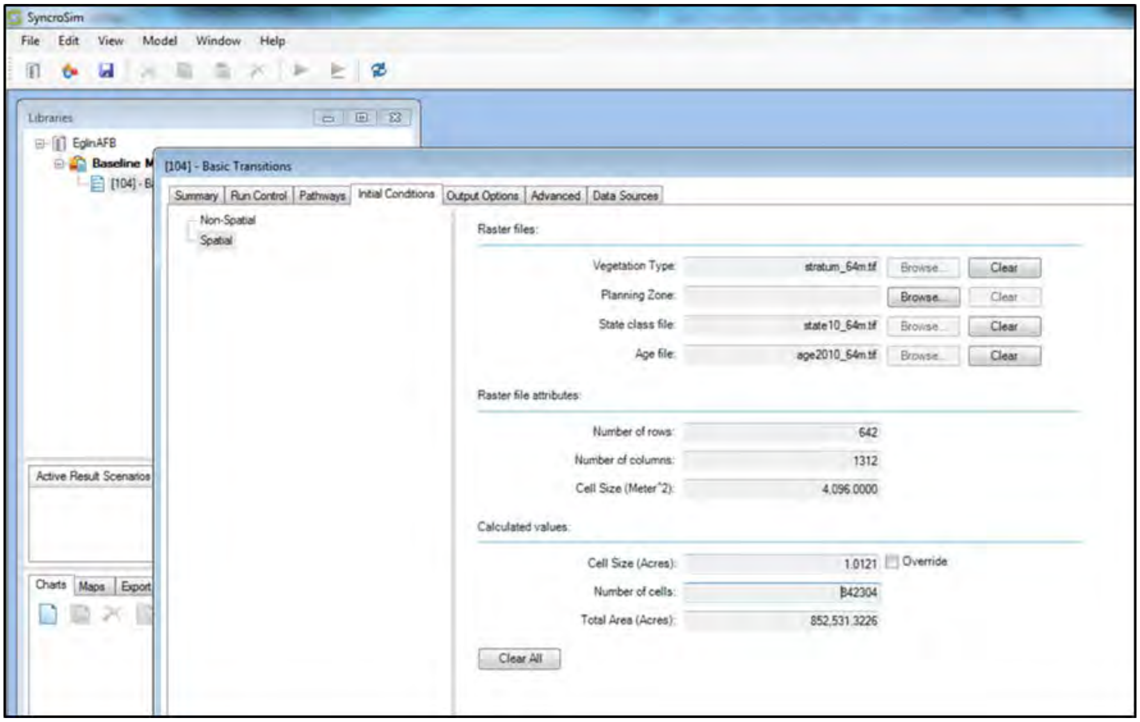
You could also import these values from an Excel file by right-clicking on the top-left cell of the distribution table and selecting “Import”. This table must have columns for

“Vegetation Type”, “State Class”, and “Relative Amount”, and all landscape state names must be identical in spelling and format to those in the Project Definitions for the model.



If you choose to run a spatially explicit simulation (the box in the previous screen was checked), click on “Spatial” to the left of this window. Here, a series of Geo.TIFF maps must be uploaded, which together show the underlying stratum map (“Vegetation Type”), the distributions of each landscape state (“State class file”), and the ages of each landscape cell (“Age file”). For each file type in this window, click “Browse”, navigate to the appropriate file, and click “Open” to upload the correct Geo.TIFF map. For the “Basic Transitions” scenario, do not upload a map for “Planning Zone”. See *Section 8. Landscape Input Values and Maps in ArcGIS* for guidance in creating these input maps. All maps uploaded in this step must have the same extents (i.e., number of rows and columns) and cell sizes. If this is not the case, an error message will appear, and the simulation will not run.

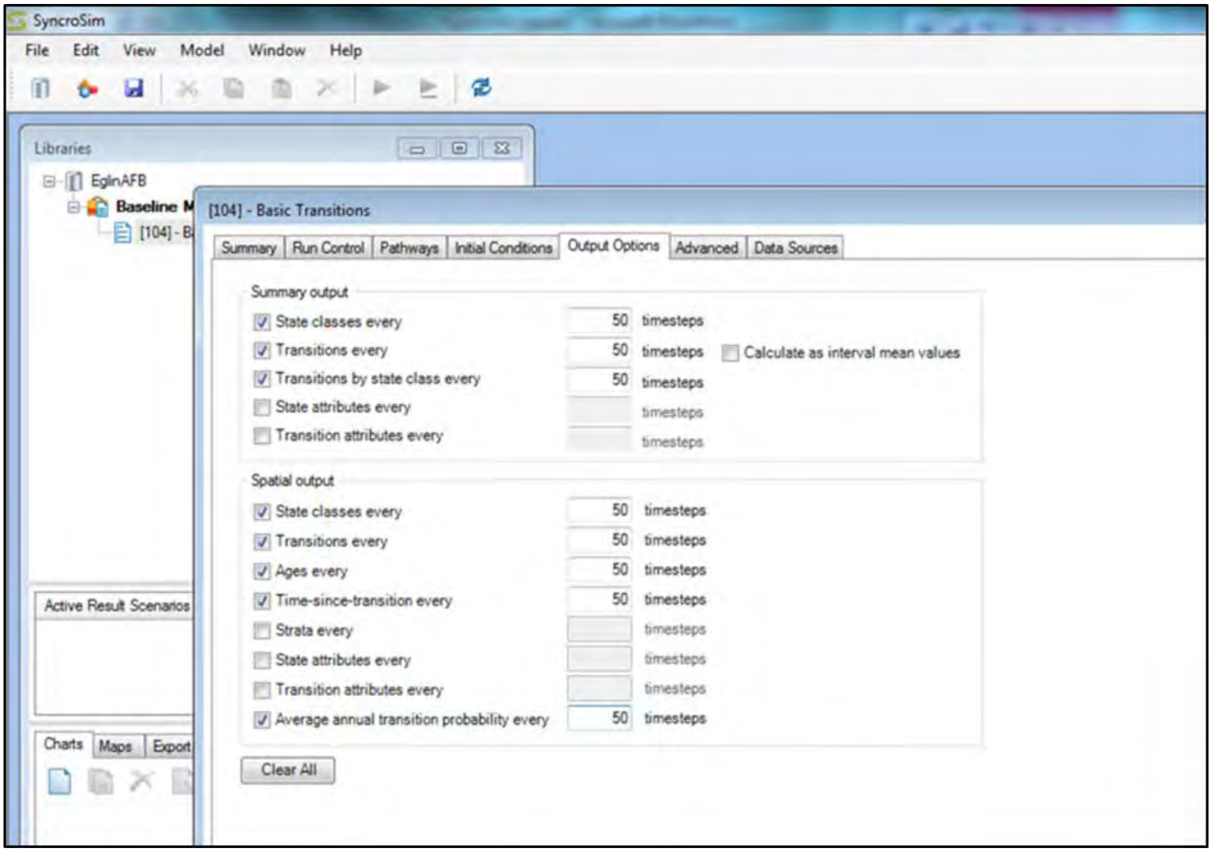
The ST-SIM program will then automatically calculate appropriate values for the numbers of rows and columns, the cell size, the number of cells, and the total landscape area based on the attributes associated with the uploaded map files.



4.5.3 Output options

To set the final simulation controls in ST-SIM, click on the tab "Output Options" in the "Basic Transitions" window. On this screen you can indicate what types of outputs you would like the model to generate throughout a simulation and at what point(s) in the simulation you would like those outputs created. For example, if you select "State classes every 1 time step(s)" for both the Summary and Spatial Outputs, the model will track the area and location of every state class for every iteration (depending on the number of iterations given in the "Run Control" tab) and time step of the simulation. If you select "State classes every 50 time steps", however, the model will only save that information for the 50^{th} time step (for every iteration).

In non-spatial simulations, the summary outputs are the only available output options (see selection possibilities in the "Summary output" box on the "Output Options" screen). However, in a spatially explicit simulation (i.e., Geo.TIFF maps have been uploaded to parameterize the model's initial conditions), the user can choose to select spatially explicit outputs (see selection possibilities in the "Spatial output" box on the "Output Options" screen). These outputs include maps of the landscape showing the locations of state classes and transition events for the specified times steps and iterations.



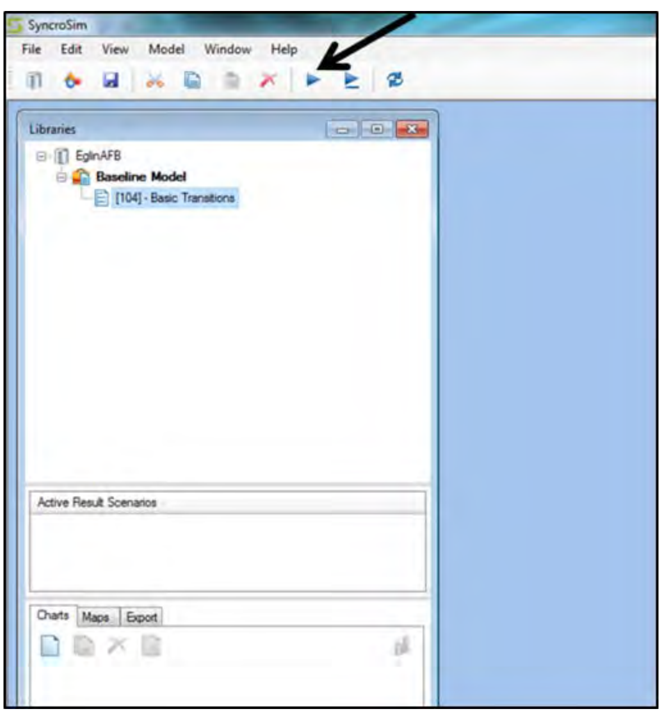
See Table D-1.14 for a description of each major available output. Click on the box next to one or more output names; each checked output will be produced during the course of the ST-SIM simulation. The simulation running time will be a function of the number of outputs you select, whether or not you produce output maps, the number of iterations you run, and how often you want outputs produced.

Table D-1.14 Available outputs from an ST-SIM model. Spatial outputs can only be produced for spatially explicit simulations where Geo.TIFF files have been uploaded to parameterize the model's initial conditions.

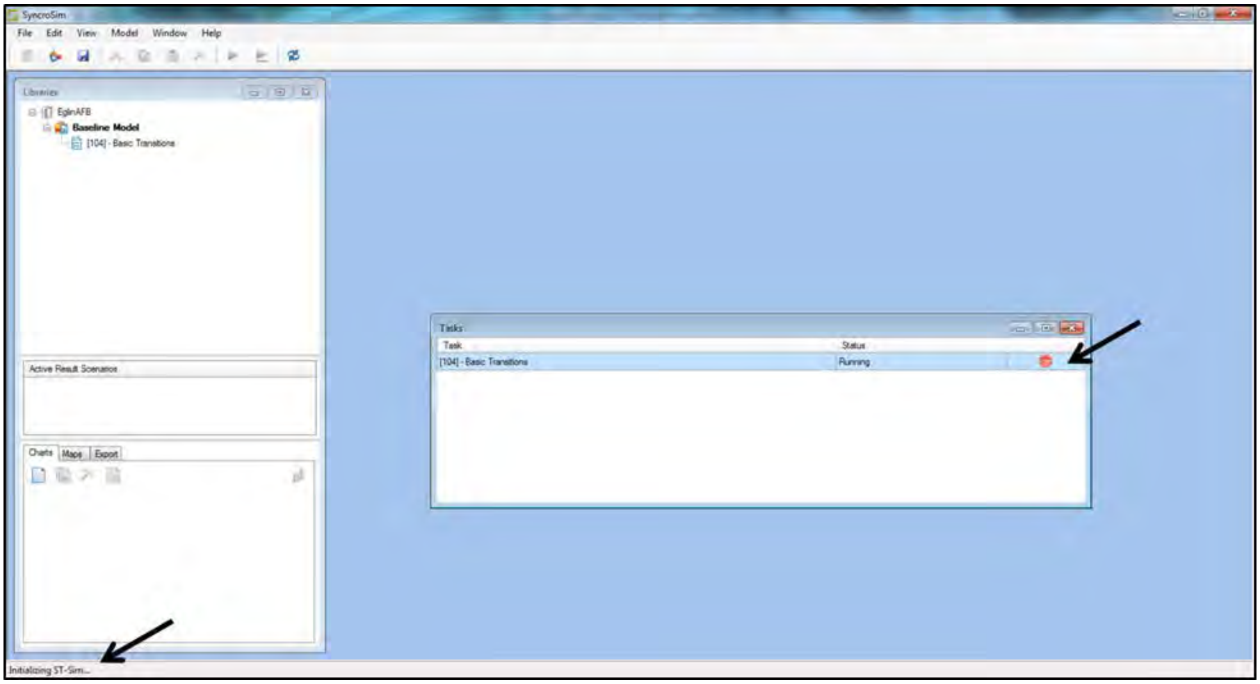
Output Name	**Description**
Summary Outputs	*Format: Exported as Microsoft Excel files*
State classes	Area of the landscape in each state class (for iterations and time steps chosen)
Transitions	Area of the landscape affected by each transition type (for iterations and time steps chosen)
Transitions by state class	Area of each state class affected by each transition type (for iterations and time steps chosen)
Spatial Outputs	*Format: Exported as Geo.TIFF files*
State classes	Map of landscape showing state classes, produced for each iteration and time step indicated
Transitions	Map of landscape showing the locations of specific transition types; produced for each iteration and time step indicated. An individual map is produced for each transition type.
Ages	Map of landscape showing the "age" of each landscape cell; applicable primarily for forest stands

5. Running an ST-SIM Model

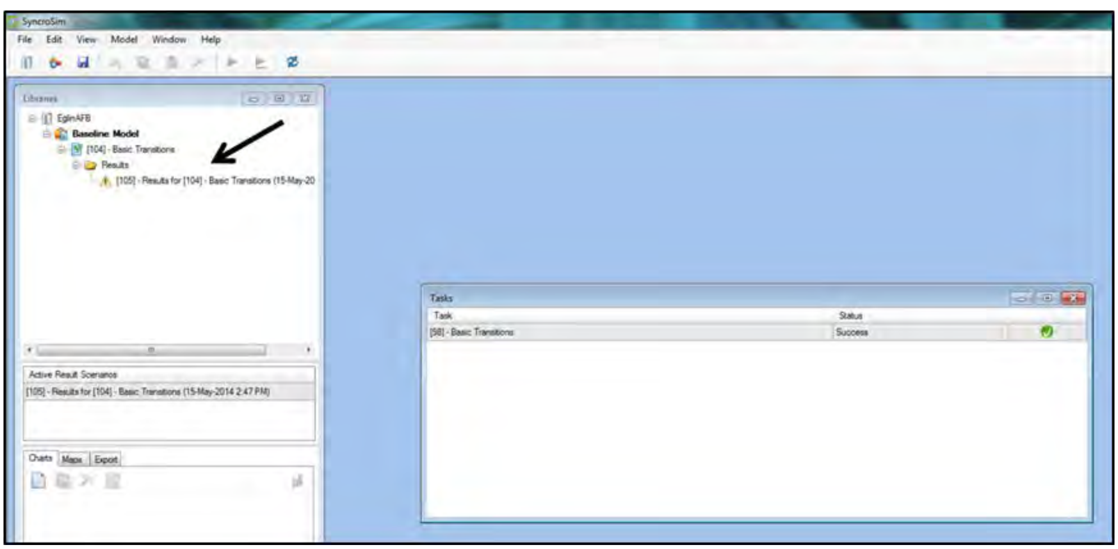
after all states, transitions, input values (or maps), and other parameters have been added to the ST-SIM model, you are ready to simulate your landscape model. Highlight the scenario name in the "Libraries" window (for example, "Basic Transitions"), and click on the "Run" button along the menu bar at the top of the "SyncroSim" screen.



After you hit the run button, a task window should appear indicating that the model is running, and a simulation bar at the bottom of the screen indicates the current iteration and time step that the model is on. The simulation can be stopped at any time by clicking the “Stop” symbol in the task window.



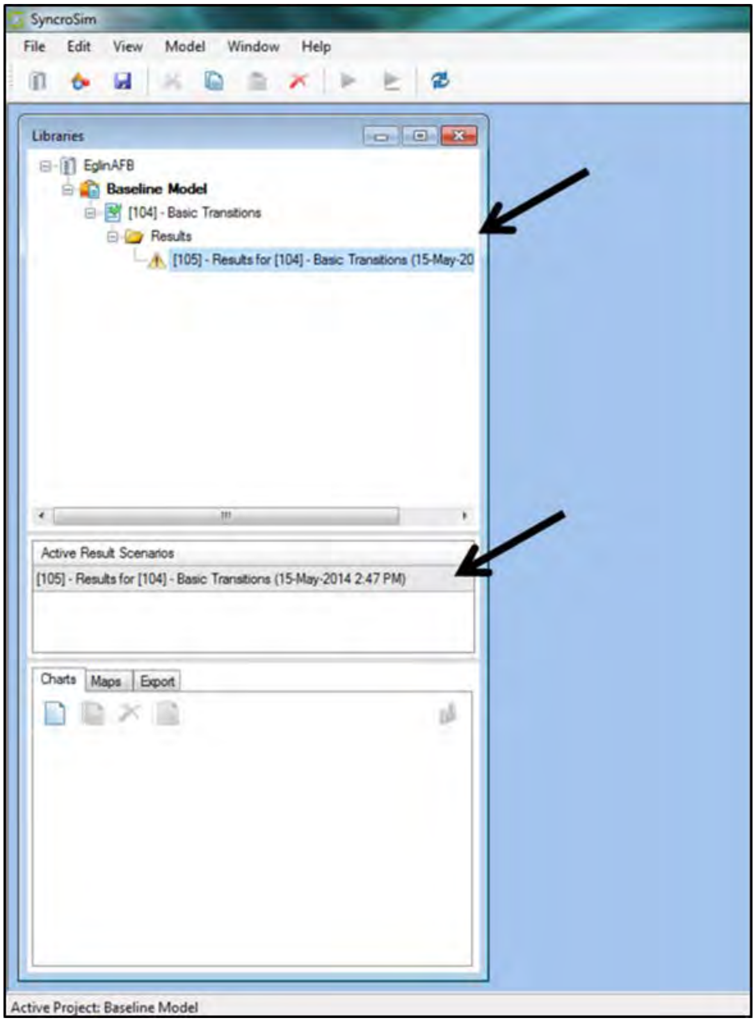
When the simulation has completed, the status should read “Success” in the “Task” window, and a results folder will appear under the transition name in the “Libraries” window.



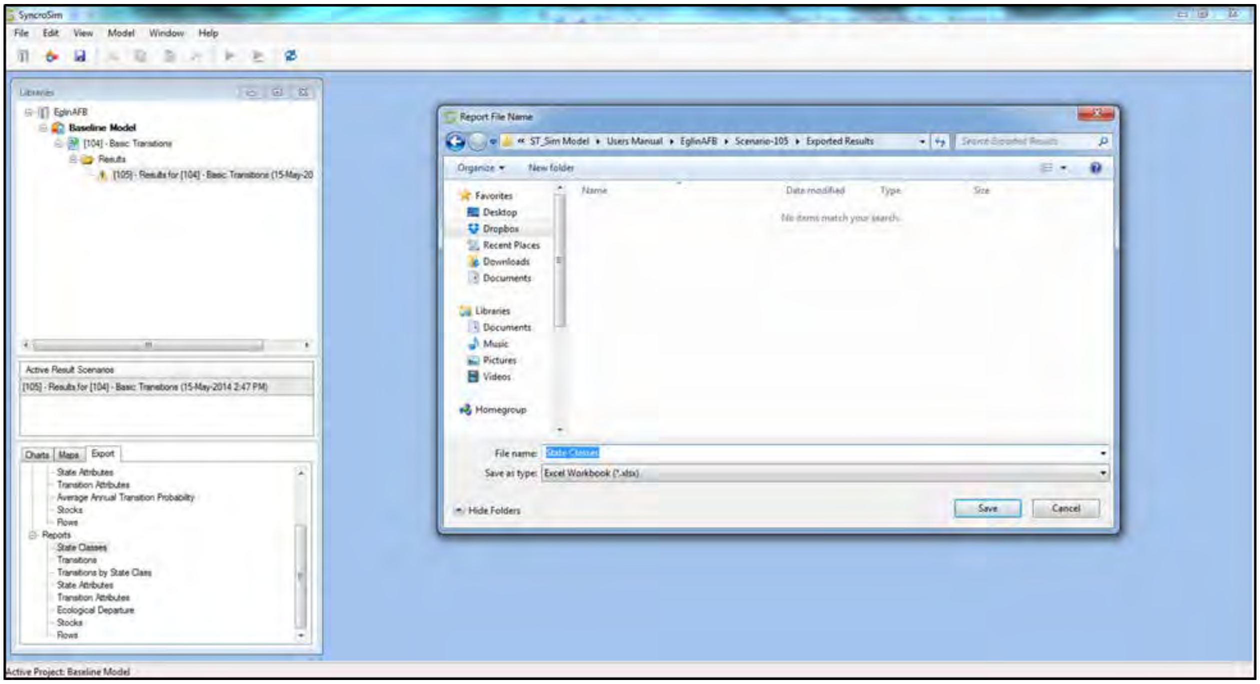
6. ST-SIM Results and Outputs

After the simulation has completed, the user can either view results within the ST-SIM program, export tables for viewing in other programs (like Microsoft Excel), or open Geo.TIFF maps in a GIS platform (e.g., ArcGIS).

Click on the appropriate results listed under the scenario name (here, “Basic Transitions”) in the “Libraries” window. This will make those particular results the “active” results if more than one results folder is available.



To generate a report, click on the “Export” tab at the bottom of the “Libraries” window, double click on the type of report you would like to create (in this example, “State Classes”), and save the new report. This will create a Microsoft Excel file showing, for example, the area of each state class for every iteration (depending on the number of iterations you chose in the “Run Control” tab) and every time step you selected in the “Output Options” tab.

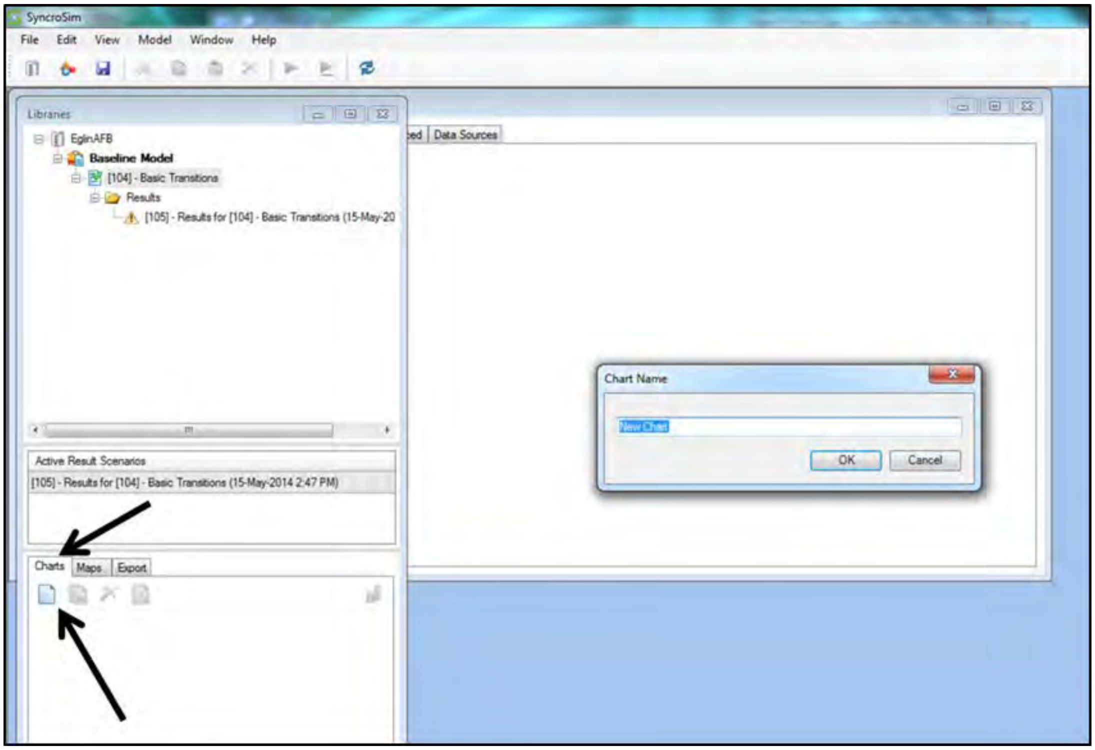


If the model was parameterized as spatially explicit, maps showing the locations of landscape states and specific transitions can also be produced. Click on the "Export" tab at the bottom of the "Libraries" window, double click on the type of map you would like to create (in this example, "State Classes"), and browse to or create a folder where maps will be saved. The ST-SIM model will then produce maps of the specified category (e.g., state classes, transitions) for every iteration (depending on the number of iterations you chose in the "Run Control" tab) and every time step you selected in the "Output Options" tab. The names of each map produced contain information about the scenario, model iteration, model time step, and map type (Figure D-1.9).

Figure D-1.9 An example of an identification name associated with result maps produced through the ST-SIM model.

These maps can then be opened in a mapping platform like ArcGIS (see *Section 8. Landscape Input Values and Maps in ArcGIS*).

Results exported as Reports and Maps can also be viewed within the ST-SIM model as a "Chart" by clicking the "Charts Tab" and selecting the "Blank Chart" icon. You can then double-click on the new chart name to add results that you would like to view within the program.



7. Advanced Model Parameterization – Spatial Multipliers

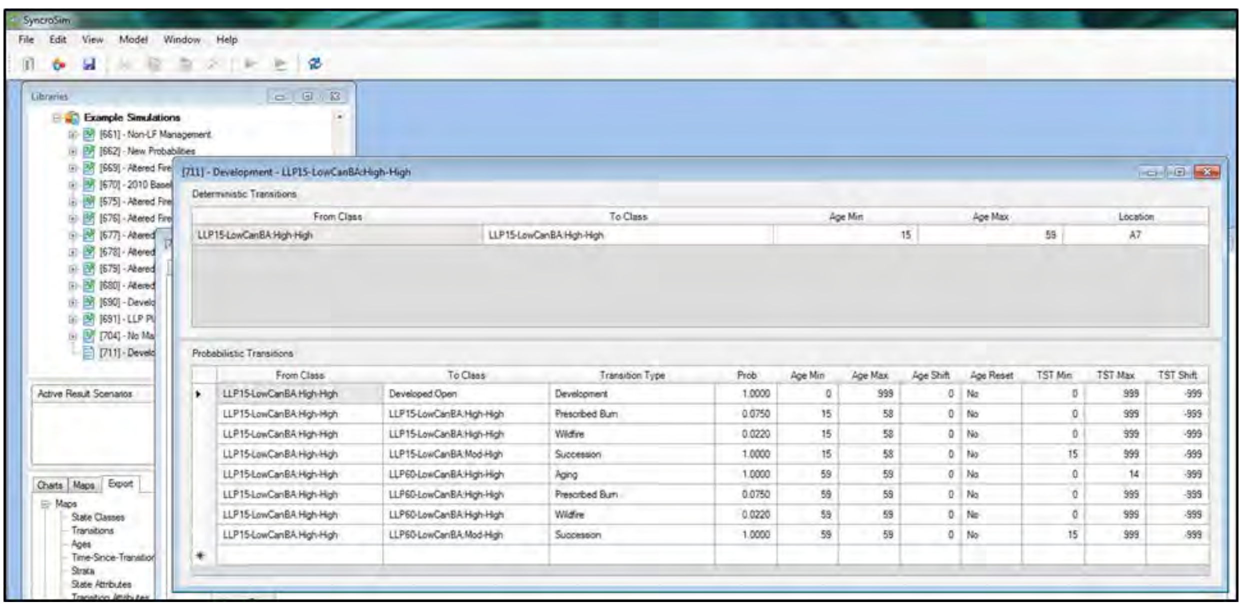
In addition to the baseline parameters discussed in the preceding sections, the user can also choose to add a number of more advanced parameters or processes to the ST-SIM landscape model of Eglin AFB. In this section, we describe how transitions can be constrained within specific locations in the study region or to specific time steps throughout a simulation.

For some transitions, the user may wish to constrain those events to specific areas. For example, a user may wish to determine the impact of a development project in a particular area of the base on the entire RCW population. Similarly, a user may wish to better understand how focusing limited management resources into one area might impact the availability of suitable habitat for RCWs. Adding a spatial constraint to a transition event in the ST-SIM landscape model is done through the use of spatial multipliers under the "Advanced" tab in the scenario window.

As an example, let's assume that you want to predict RCW habitat availability over 20 years, given that a potential development project will convert all landscape cells within a 36,736 acre plot in the western half of the base to the Developed state class in year 10 (Figure D-1.10a). In order to parameterize this scenario, a transition group containing the Development transition must be created in the project definitions for this scenario. This group has already been created for the baseline model (described in *Section 4.2 Transitions*).

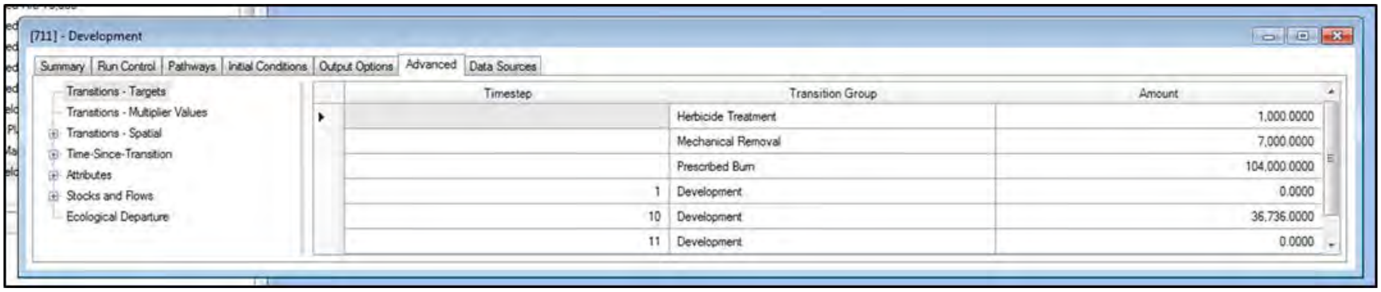
Next, a probabilistic value for the Development transition must be added to every landscape state in the same manner that, for example, the fire transition was added to the Longleaf Pine landscape states. For probability, you can use any value, as long as all landscape states have the same value (unless you want to parameterize the model such that some landscape states have a higher probability of being developed than others, in which case you would give landscape states that will be preferentially converted a higher probability). For simplicity, we recommend using a probability of 1.

Add this transition by clicking on a state class box (for example, LLP15-LowCanBA:High-High). In the “From Class” dropdown under “Probabilistic Transitions”, select the state class to which this window belongs (in this example, “LLP15-LowCanBA:High-High”). Select “Developed” under “To Class”, “Development” under “Transition Type”, and “1” under “Prob”. Because age does not matter here, simply input “0” and “999” for “Age Min” and “Age Max”, respectively. Finally, input “-999” under “Age Shift”, “Yes” under “Age Reset”, “0” under “TST Min”, “999” under “TST Max”, and “-999” under “TST Shift”. In this example, these inputs specify that a landscape cell containing a longleaf pine stand in the state class LLP15-LowCanBA:High-High will move to the Developed state class due to the Development transition with certainty, no matter how long it has been since a disturbance last occurred. When this happens, the age of the stand (or landscape cell) will reset to 0. This transition should be added to all landscape states (except Water) with identical parameters (with the exception of the “From Class” field). Given this parameterization alone, all landscape cells would be converted to the Developed state during a simulation. Therefore, we also need to set transition targets and use a spatial multiplier file to further govern this transition.



Development targets are used here to tell the model when to turn the Development transition on and off. In the scenario window, click on the “Advanced” tab, and select “Transitions-Targets” on the menu along the left-hand side of the screen. In the table to the right, click in the cell in the top left corner and select “Time Step” in the dropdown list that appears. This should add a column for “Time Step” to the Transition Target table. Next, choose “Development” in the dropdown for “Transition Group”, “1” under “Time Step”, and add “0”

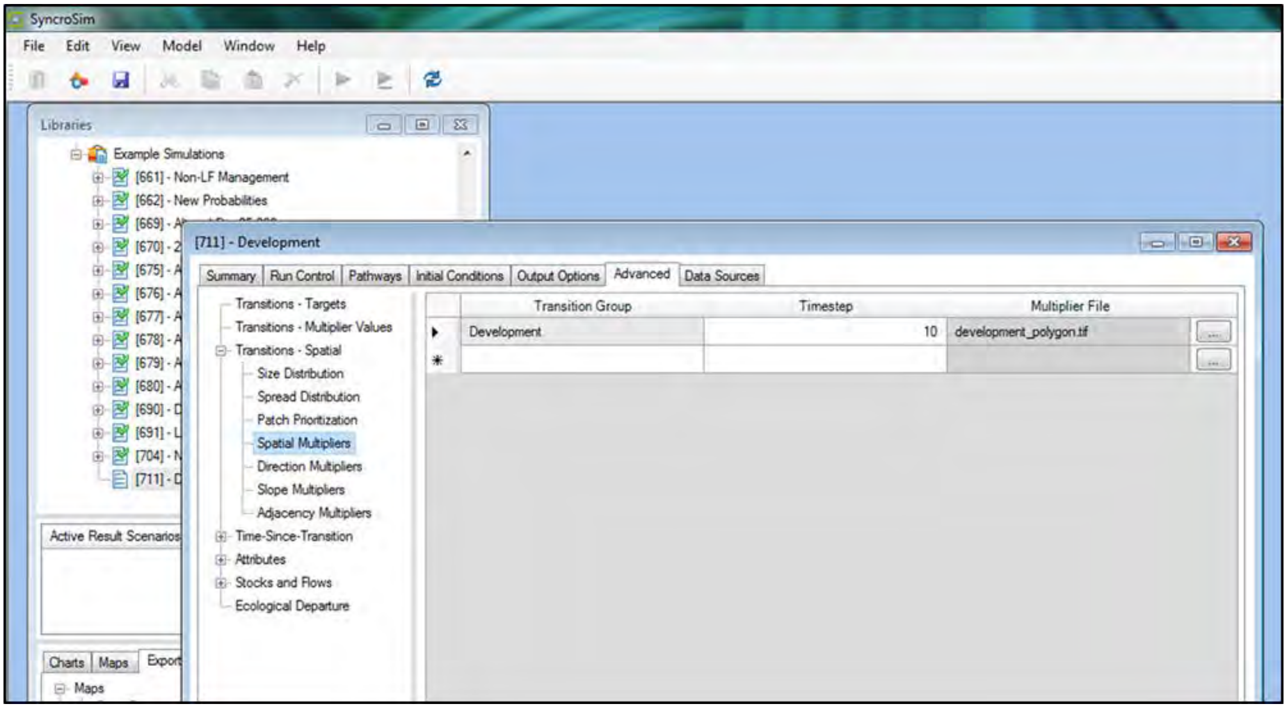
under “Target Area (Acres)”. Make a second transition target line for “Development”, this time inputting “10” under “Time Step” and “36,736” under “Target Area (Acres)”. Finally, make a third transition target line for “Development”, this time inputting “11” under “Time Step” and “0” under “Target Area (Acres)”. This parameterization tells the model to turn off the Development transition from time step 1 through time step 9, to simulate Development over 36,736 acres at time step 10, and then to turn Development off again from time step 11 through the end of the simulation.



In the final parameterization step for this option, you then need to upload a Geo.TIFF map that will act as a spatial multiplier. In ArcGIS, create a raster file where all cells that should be developed during the simulation have a value of “1” and all cells that should not be developed a value of “0”. This raster must be in the same projection and have the same size and extent as the Geo.TIFF files used to initialize the model. Export this raster file as a Geo.TIFF. See Figure D-1.10a for an example of what this spatial multiplier landscape map should look like.

Figure D-1.10 An example of spatial multiplier files (file type: Geo.TIFF) used to spatially constrain (a) development and (b) all forest management transitions within a specific area on Eglin AFB.

Next, go to the “Advanced” tab in the scenario window, expand the list for “Transitions – Spatial”, and click on “Spatial Multipliers”. Select “Development” under “Transition Group” and “10” under “Time Step”. Finally, browse to the spatial multiplier Geo.TIFF file.

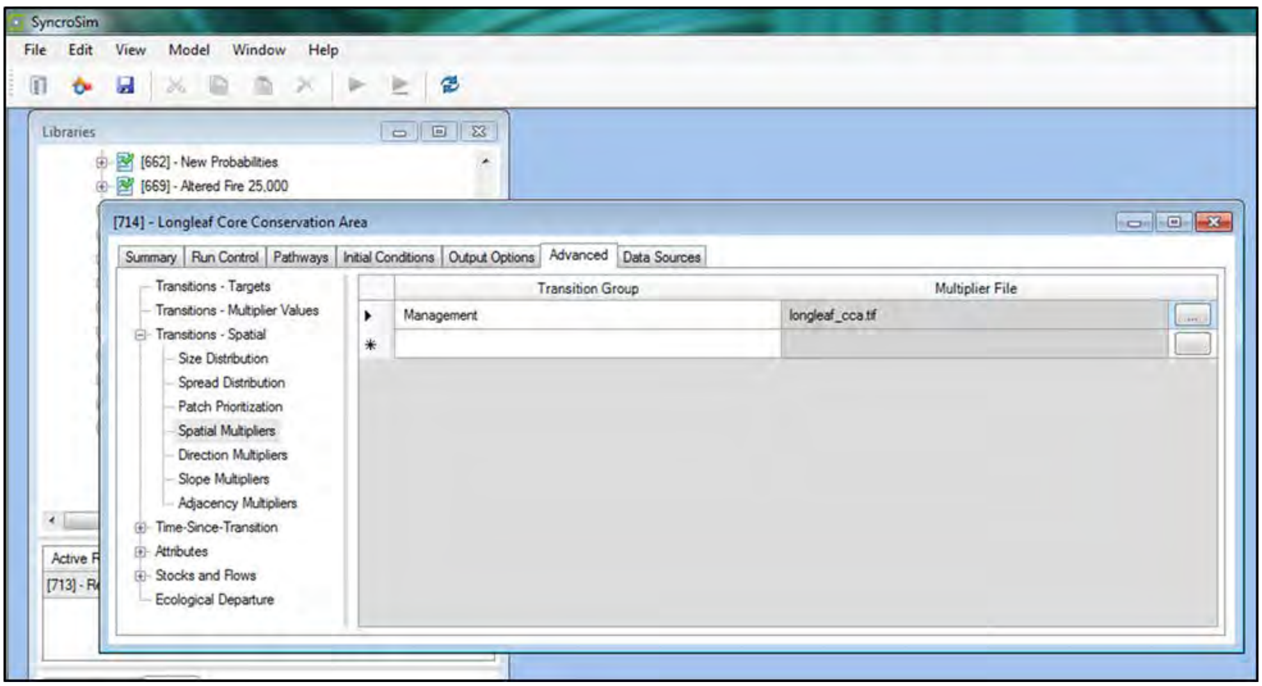


Under this parameterization, the Development transition will be “turned on” at the time step when the Development target is greater than 0 (here, time step 10). When this transition is turned on, the ST-SIM model will evaluate each landscape cell such that the cell’s state-specific probabilities for all transitions in the transition group selected in the Spatial Multipliers table (in this example, Development) are multiplied by the cell’s corresponding spatial multiplier value given in the Spatial Multiplier Geo.TIFF. For example, consider a landscape cell characterized by the Young Pine state that is within the development polygon shown in Figure D-1.10a. Because the Development transition target is 0 for all time steps prior to time step 10, this cell will not experience the Development transition from time steps 1 through 9. However, at time step 10, the cell’s Development transition probability (in this example, 1) will be multiplied by the spatial multiplier given for that cell in the Spatial Multiplier map (in this example, 1), and the state of the landscape cell will be converted to the Developed state class with a probability of 1 (i.e., 1 * 1 = 1). The transition probabilities (probability = 1) for all cells outside of the development area will be multiplied by 0 (based on the value of the spatial multiplier Geo.TIFF), resulting in a Development transition probability of 0 (i.e., these cells will not be converted to the Developed state). Finally, because the Development transition target is 0 for all time steps after time step 10, no landscape cells anywhere in the landscape will be developed from time step 11 on, irrespective of their spatial location.

For a second example, assume that you want to evaluate the impacts of conducting all landscape management actions (e.g., prescribed fire, herbicide application, and mechanical removal) within the LCCA at Eglin AFB (Figure D-1.10b). For this scenario, the majority of required parameters have already been added within the baseline model. For instance, the Prescribed Burn, Herbicide, and Mechanical Removal transitions were previously lumped into

the Transition Group "Management" in *Section 4.2 Transitions,* and all state-specific transition probabilities and targets for these transitions were added as part of *Section 4.3 Organization of States and Transitions*. As a result, you only need to add the spatial multiplier Geo.TIFF file (shown in Figure D-1.10b), where landscape cells within the core conservation area are given a value of "1" and those outside the area a value of "0".

Go to the "Advanced" tab in the scenario window, expand the list for "Transitions – Spatial", and click on "Spatial Multipliers". Select "Management" under "Transition Group", and browse to the spatial multiplier Geo.TIFF file. Because we are not constraining management to the core conservation area during specific time steps, values under the "Time Step" column do not need to be added with either the transition targets or the spatial multiplier file. During the simulation for this scenario, each cell's transition probabilities for all transitions falling within the Management transition group will be multiplied by the overlaying spatial multiplier file (i.e., * 1 or 0), and these transitions will only occur when the resulting probability is greater than 0.



This procedure can also be used to simulate a variety of other scenarios. For instance, instead of using only values of 0 and 1 to turn transitions on and off, you can give landscape cells in the spatial multiplier Geo.TIFF file values between 0 and 1 to increase the probabilities that certain landscape cells will experience specified transitions over others (much in the same way we centered management activities within the LCCA in the above example). Using this parameterization, transitions would still occur outside of the specified area, just at a lower probability.

In addition, the ST-SIM platform has many other capabilities not described here. For example, the impacts of hurricanes and the spread of invasive species (e.g., sand pines), diseases, and insect infestations can also be considered. Although we do not describe the parameterization for these events here, go to the Apex RMS website (http://www.apexrms.com) for more information.

8. Landscape Input Values and Maps in ArcGIS

To run a meaningful simulation of the ST-SIM model, an understanding of the landscape's composition is critical when initializing the model. If you plan to run a non-spatial version of the model, you will need to know the percentage of the total landscape in each landscape state used in the model. In this scenario, the landscape's composition is important, but the spatial distribution of those states will not be considered. On the other hand, a spatially explicit simulation of the model will require that you upload maps of the study area that show both the composition and distribution of the landscape states.

We created maps in ArcGIS v. 10 (ESRI) to convey this information for Eglin AFB These maps were necessary for calculating the landscape composition for the non-spatial simulation and for providing the necessary parameters for the spatially explicit simulation. The state class map was used to determine the landscape composition (non-spatial simulation) while the stratum, state class, and age maps were used to parameterize the spatially explicit simulation.

All maps required to initialize an ST-SIM landscape model for Eglin AFB have been created, representing base characteristics for the year 2010. These files, in both Geo.TIFF and raster formats, can be found in the sub-folders "Exported ST-SIM initialization maps" and "Eglin Maps – Rasters", respectively, contained in the zip folder accompanying this guide.

8.1 State class map

We began by creating a state class layer in ArcGIS for the full landscape, which categorized every landscape cell as one of the landscape states we created in our parameterization of the ST-SIM model. Given how we categorized the landscape states in ST-SIM, we needed to combine information on the landcover type, age (for Longleaf Pine states), structural stage (to differentiate the mid-story and understory conditions for Longleaf Pine states), and the cover type (to differentiate the canopy BA categories for Longleaf Pine states). Personnel at Jackson Guard, the natural resource management office at Eglin AFB, provided us with recent ArcGIS layers for landcover (years: 1994-2010), stand age (year: 2005), fire history (years: 1986-2010), and stand characteristics (year: 2010).

We first converted the landcover layer to a raster layer (cell size: 30 m x 30 m) and reclassified the original landcover types to categories that were relevant to our ST-SIM model (Table A-1.15). We also gave each new landcover category a special identification code for use when combining this landscape layer with others in ArcGIS. We saved this map as "landcover2010".

Table D-1.15 Reclassification of the original landcover map (year: 2010) provided by personnel at Jackson Guard (Eglin AFB) for use in creating the state class map for input into the ST-SIM model.

Original Landcover Category (map value)	**ST-SIM Landcover Category**	**Identification Code**
No Data	No Data	No Data
Developed (1)	Developed	100,000
Grassland[1] (2)	Bare Land[1]	800,000
EF-Longleaf (3)	Longleaf Pine	300,000
EF-Sandpine (4)	Sandpine	400,000
EF-Mixed (5)	Mixed	500,000
SS-Evergreen (6)	Mixed	500,000
SS-Mixed (7)	Mixed	500,000
Bare Land (8)	Bare Land	800,000
Emergent Vegetation (9)	Young Pine	200,000
BLF-Evergreen (10)	Hardwood	600,000
BLF-Deciduous (11)	Hardwood	600,000
BLF-Mixed (12)	Hardwood	600,000
BLF-SS (13, 14)	Hardwood	600,000
Mixed Forest (deciduous, evergreen, scrub; 15)	Mixed	500,000
Water (16)	Water	700,000
Shoreline and Bare Land (17)	Bare Land	800,000

[1]At Eglin, the majority of areas classified as "grassland" are open areas used for military testing and training. As such, they are maintained as opened areas that would never experience succession, and we accordingly classified these areas as "Bare Land".

Next, we created an age category layer using the original ArcGIS vector layer for stand ages provided by Jackson Guard, which indicated the ages of all forested stands on the base as of the year 2005. We converted the vector layer to a raster layer and added 5 years to all ages to approximate the stand ages for the year 2010. In doing so, we assumed that no stand-clearing fires, development projects, or other landcover changes reverted a stand's age back to zero. However, such events could have occurred within the period from 2005-2010, and we may have overestimated the ages of some stands (although we do not believe that this impacted simulation results, because such changes to the landscape would have altered the landcover state to a non-longleaf pine state where age is irrelevant). We then reclassified this age layer so that all stands fell into one of three categories (with an associated identification value): (1) age 0-14 (ID: 10,000), (2) age 15-59 years (ID: 20,000), and (3) age $\geq$ 60 years (ID: 30,000). We saved this layer as "age2010_cats" (for "age categories in 2010").

We then used the fire history vector layer to approximate the structural stage characteristics for all longleaf pine stands on the base. In its original form, the fire history layer indicated the number of years since the most recent fire for all stands on the base. We converted this vector layer to a raster and reclassified the layer such that all cells fell into one of four categories: (1) 0-15 years since fire (ID: 1,000), (2) 16-20 years since fire (ID: 2,000), (3) 21-35 years since fire (ID: 3,000), and (4) > 35 years since fire (ID: 4,000). Based on this categorization, we assumed that landscape cells that were burned within 15 years would fall into

the “high midstory suitability – high understory coverage” (High-High) structural stage, that cells that have been burned in 16-20 years would fall into the “moderate midstory suitability – high understory coverage” (Mod-High) structural stage, that cells that have been burned in 21-35 years would fall into the “moderate midstory suitability – low understory coverage” (Mod-Low) structural stage, and that cells that have not been burned in over 35 years would fall into the “low midstory suitability – low understory coverage” (Low-Low) structural stage. We saved this layer as “TSB2010” and ensured that its map attributes matched those of the landcover layer.

We used the stand characteristics vector layer provided by Jackson Guard to determine the canopy BAs for longleaf pine states. We converted this stand characteristics layer to a raster layer, using the “Basal Area” column in the attribute file as the primary raster value used in the conversion. In this converted raster file, all cells on the landscape were given a value for the canopy BA in ft^2/ac. We then reclassified this layer so that all cells fell into one of three categories for canopy BA: (1) low canopy BA (< 10 ft^2/ac; ID: 100), (2) suitable canopy BA (10-70 ft^2/ac; ID: 200), and (3) high canopy BA (> 70 ft^2/ac; ID: 300). These categories corresponded to the canopy BA cover type values used to differentiate Longleaf Pine states in the ST-SIM model. We saved this layer as “Eglin_BA” and ensured that its map attributes matched those of the landcover layer.

We then created the state class layer by combining the modified layers for landcover type, stand age, fire history, and stand characteristics using the Raster Calculator in ArcGIS according to the following equation:

landcover2010 + age2010_cats + TSB2010 + Eglin_BA = State Class (saved as “state_temp”)

Given the identification scheme we used for the attributes in each of these layers, we could differentiate the state class of each cell on the landscape. In the new identification number, the hundred-thousand digit indicates the landcover type, the ten-thousand digit indicates the age category, the thousand digit indicates the structural stage (via the time since fire), and the hundred digit indicates the cover type (via the canopy BA; Figure D-1.11).

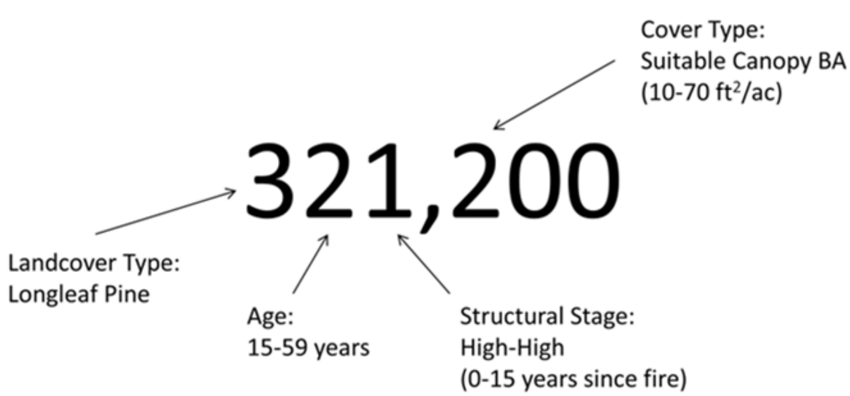


Figure D-1.11 An example of an identification number associated with landscape cells in the “state_temp” ArcGIS raster layer, which combined layers for landcover type, stand age, fire history, and stand characteristics. The hundred-thousand digit indicates the landcover type, the ten-thousand digit indicates the age category, the thousand digit indicates the structural stage (via the time since fire), and the hundred digit indicates the cover type (via the canopy BA). The

example identification number shown here would correspond to the state "LLP15-SuitCanBA:High-High" in the ST-SIM model.

We reclassified the values in the "state_temp" layer so that the state names and identification values corresponded with those used to parameterize the ST-SIM model (Table D-1.16). This step was important for a two reasons. When we combined the layers in ArcGIS to form the "state_temp" layer, landscape cells associated with non-longleaf pine states were given values for age category, structural stage, and cover type, which are not relevant for non-longleaf pine states in our ST-SIM model for Eglin AFB. As a result, we needed to reclassify the values in this combined state class layer so that the values for non-longleaf pine cells (i.e., any cell with a value not in the 300,000s) were rounded to the hundred-thousand digit. We also needed to reclassify all identification values so that they matched the appropriate state class values used to parameterize the states in the ST-SIM model. This reclassified layer was saved as "state_temp2" for the final processing steps.

Table D-1.16 Reclassification system for the cell values in the layer "state_temp" that resulted from the combination of layers for landcover, age category, fire history, and stand characteristics. Note, because we used the time since fire to approximate the midstory suitability and understory cover, landscape states with High midstory Suitability and Low understory cover (High-Low) were not discerned in this classification scheme.

Original Cell Value	**New Reclassified State (for use in ST-SIM)**	**New Reclassified Identification**
100,000 – 199,999	Developed:Open	600
200,000 - 299,999; 310,000 – 314,300	Young Pine:Open	250
400,000 – 499,999	Sand Pine:Closed	500
500,000 – 599,999	Mixed:Closed	300
600,000 – 699,999	Hardwood:Closed	400
700,000 – 799,999	Water:Open	700
800,000 – 899,999	Bare Land:Open	800
321,100	LLP15-LowCanBA:High-High	10
---------	LLP15-LowCanBA:High-Low	11
322,100	LLP15-LowCanBA:Mod-High	20
323,100	LLP15-LowCanBA:Mod-Low	30
324,100	LLP15-LowCanBA:Low-Low	40
321,200	LLP15-SuitCanBA:High-High	50
---------	LLP15-SuitCanBA:High-Low	51
322,200	LLP15-SuitCanBA:Mod-High	60
323,200	LLP15-SuitCanBA:Mod-Low	70
324,200	LLP15-SuitCanBA:Low-Low	80
321,300	LLP15-HighCanBA:High-High	90
---------	LLP15-HighCanBA:High-Low	91
322,300	LLP15-HighCanBA:Mod-High	100
323,300	LLP15-HighCanBA:Mod-Low	110
324,300	LLP15-HighCanBA:Low-Low	120
331,100	LLP60-LowCanBA:High-High	130

---------	LLP60-LowCanBA:High-Low	131
332,100	LLP60-LowCanBA:Mod-High	140
333,100	LLP60-LowCanBA:Mod-Low	150
334,100	LLP60-LowCanBA:Low-Low	160
331,200	LLP60-SuitCanBA:High-High	170
---------	LLP60-SuitCanBA:High-Low	171
332,200	LLP60-SuitCanBA:Mod-High	180
333,200	LLP60-SuitCanBA:Mod-Low	190
334,200	LLP60-SuitCanBA:Low-Low	200
331,300	LLP60-HighCanBA:High-High	210
---------	LLP60-HighCanBA:High-Low	211
332,300	LLP60-HighCanBA:Mod-High	220
333,300	LLP60-HighCanBA:Mod-Low	230
334,300	LLP60-HighCanBA:Low-Low	240

After "state_temp" was reclassified to "state_temp2", we conducted the following processing steps. First, we exported the reclassified file so that the identification values given in Table A-1.16 were the primary values associated with the landscape cells (in ArcToolbox - "Spatial Analyst Tools" - "Reclass" - "Look-up" tool). We also used the "Majority Filter" tool in ArcToolbox to replace the value of each cell based on the majority value in their contiguous neighborhoods. This processed essentially removed outlying values and smoothed the appearance of the landcover distribution. Finally, we resampled the layer after applying the majority filter so that the resolution was changed from 30 m x 30 m to 64 m x 64 m (i.e., 1 ac). The final raster layer ("state10_64m"; Figure D-1.11) had the following attributes: (1) 1312 columns and 642 rows, (2) 64 m x 64 m (1 ac) cell size, and (3) map projection of WGS_1984_UTM_Zone_16N.

This processed layer could then be used to calculate the composition of each landscape state for use in parameterizing the initial conditions for a non-spatial simulation in ST-SIM (*Section 4.5 Simulation Controls and Initial Conditions*). In ArcGIS, you can open the attribute table for the raster layer "state10_64m" (contained in the zip folder accompanying this guide), where each row in the table is associated with a landscape state. For each state, the column "Count" indicates the number of cells in that state. By multiplying this number by the area of a single cell (here, 64 m x 64 m or 1 ac), the total area and proportion of the landscape composed of a specific state can be calculated.

To use this state layer in a spatially explicit simulation of the ST-SIM model (*Section 4.5 Simulation Controls and Initial Conditions*), the raster layer "state10_64m" needs to be exported as a Geo.TIFF file in ArcGIS. This can be done by right-clicking on the layer name in the Table of Contents in ArcGIS, selecting "Data", and then choosing "Export Data". In the "Export Raster Data" window that appears, select "Raster Dataset (original)" for both "Extent" and "Spatial Reference"; maintain the cell size as 64 m x 64 m; choose an appropriate export location for the "Location" entry; give the file an appropriate name (here, "state10_64m.tiff"); and select "TIFF" from the "Format" dropdown box. Click "Save", and the raster layer will be exported as a Geo.TIFF file to the user-specified location. See Figure D-1.12 for an example of what the state class map should look like.

8.2 Vegetation type map

To run a spatially explicit model in ST-SIM, a vegetation type map must also be uploaded under the "Initial Conditions" tab. This map delineates zones that limit what type of vegetation (and which landscape states) can occur in those areas. For example, these zones could be based on underlying soil or ecoregion types. In this model for Eglin AFB, we did not consider such zones, and individual landscape states are not limited in where they can occur. Therefore, to create this file, we converted a vector shapefile of the Eglin AFB boundary and converted it to a raster file with a cell size of 64 m x 64 m (i.e., 1 acre). This can be done in ArcGIS by opening ArcToolbox, going to "Conversion Tools" and then "To Raster", and selecting "Polygon to Raster". In the window that appears, browse to the shapefile depicting the base's area, select an appropriate value field and indicate "64" for the cell size. Depending on what you selected as the value field, you may need to reclassify the resulting raster layer so that all cells within the boundary of the base are given a single value (e.g., "1") and all cells outside of that boundary are given a value of "nodata". This map should have the same size and projection data as those associated with the state class map (1312 columns and 642 rows, 64 m x 64 m cell size, and map projection of WGS_1984_UTM_Zone_16N). As in the state class map, you must then export the vegetation map as a Geo.TIFF file in ArcGIS (see *Section 8.1 State class map*). See Figure D-1.13 for an example of what the vegetation type map should look like.

8.3 Age map

Finally, a spatially explicit ST-SIM simulation requires a map of stand ages for all relevant states. We created an age layer for the year 2010 using the original ArcGIS vector layer for stand ages provided by Jackson Guard (described in *Section 8.1 State class map*), which indicates the ages of all forested stands on the base as of the year 2005. We converted this vector layer to a raster layer with a 64 m x 64 m (i.e., 1 acre) cell size and added 5 years to all ages to approximate the stand ages for the year 2010. In doing so, we assumed that no stand-clearing fires, development projects, or other landcover changes reverted a stand's age back to zero. However, such events could have occurred within the period from 2005-2010, and we may have overestimated the ages of some stands (although we do not believe that this impacted simulation results, because such changes to the landscape would have altered the landcover state to a non-longleaf pine state where age is irrelevant). Although all landscape cells are given an age, stand ages are only relevant for landscape states where age influences the state identification or transitions (i.e., the Longleaf Pine states). This map should have the same size and projection data as those associated with the state class map (1312 columns and 642 rows, 64 m x 64 m cell size, and map projection of WGS_1984_UTM_Zone_16N). We then exported the age map as a Geo.TIFF file in ArcGIS (see *Section 8.1 State class map*). If an updated stand age vector layer is available, you would repeat these steps without altering the ages (or by altering the ages by an appropriate number of years). See Figure D-1.14 for an example of what the age map should look like.

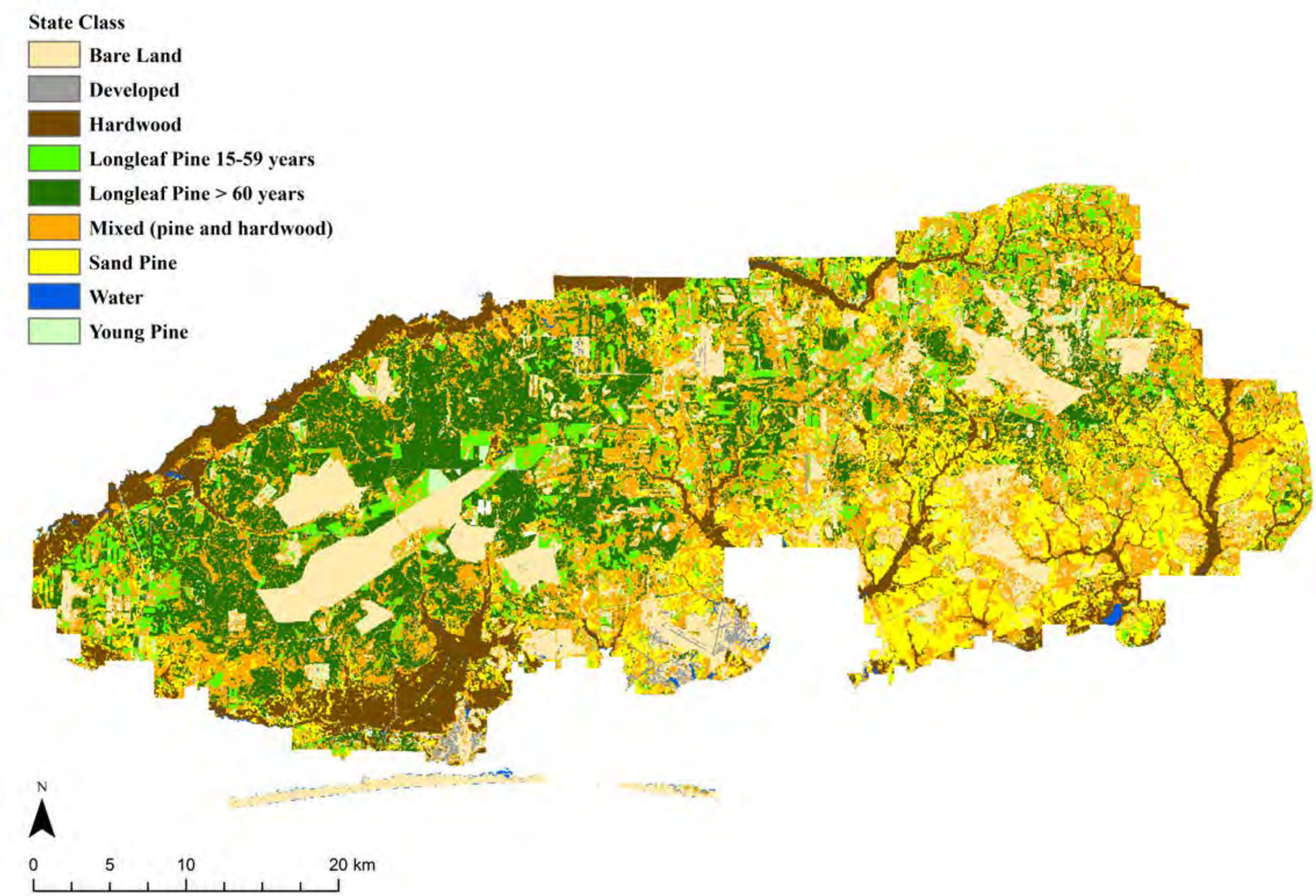


Figure D-1.12 An example of a state class map that could be uploaded as the “State class file” under the “Initial Conditions” tab to run a spatially explicit model in ST-SIM. In general, this raster file (file type: Geo.TIFF) should depict every landscape cell in the study area as one of the user-specified ST-SIM states. (Note: this map depicts the states found on Eglin AFB in 2010. For use in the model, the longleaf pine categories shown here were actually broken down in the series of longleaf pine states described in section *4.1 Landscape States*. These states were grouped as “Longleaf Pine 15-59 years” and “Longleaf Pine >60 years” here for ease of viewing).

Figure D-1.13 An example of a vegetation type map that could be uploaded as the "Vegetation Type" raster file under the "Initial Conditions" tab to run a spatially explicit model in ST-SIM. In general, this raster file (file type: Geo.TIFF) delineates zones the limit what type of vegetation (and which landscape states) can be present in those areas. In the model for Eglin AFB, we did not consider such zones, and individual landscape states are not limited in where they can occur. Therefore, all cells within the area of the base where given a single value while those found beyond the base boundary were given a value of "nodata".

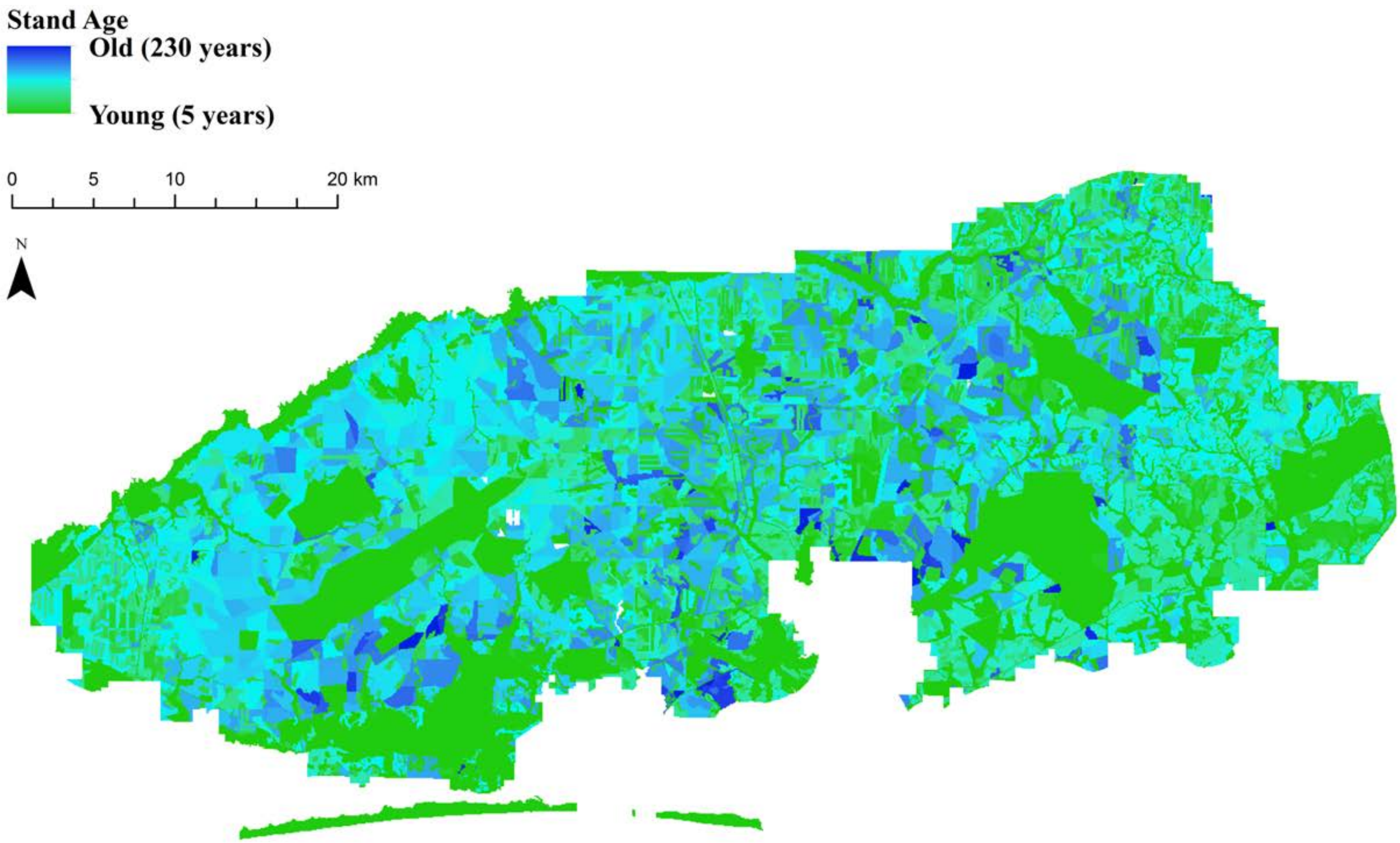
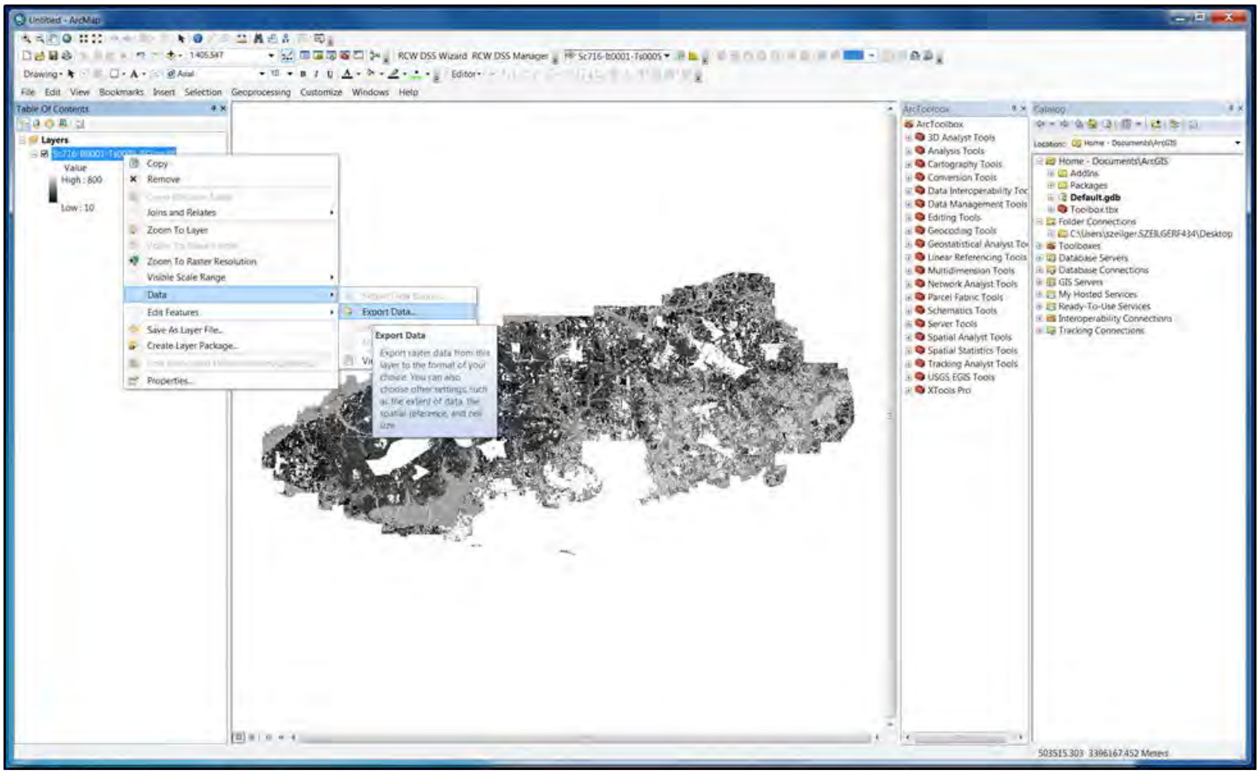


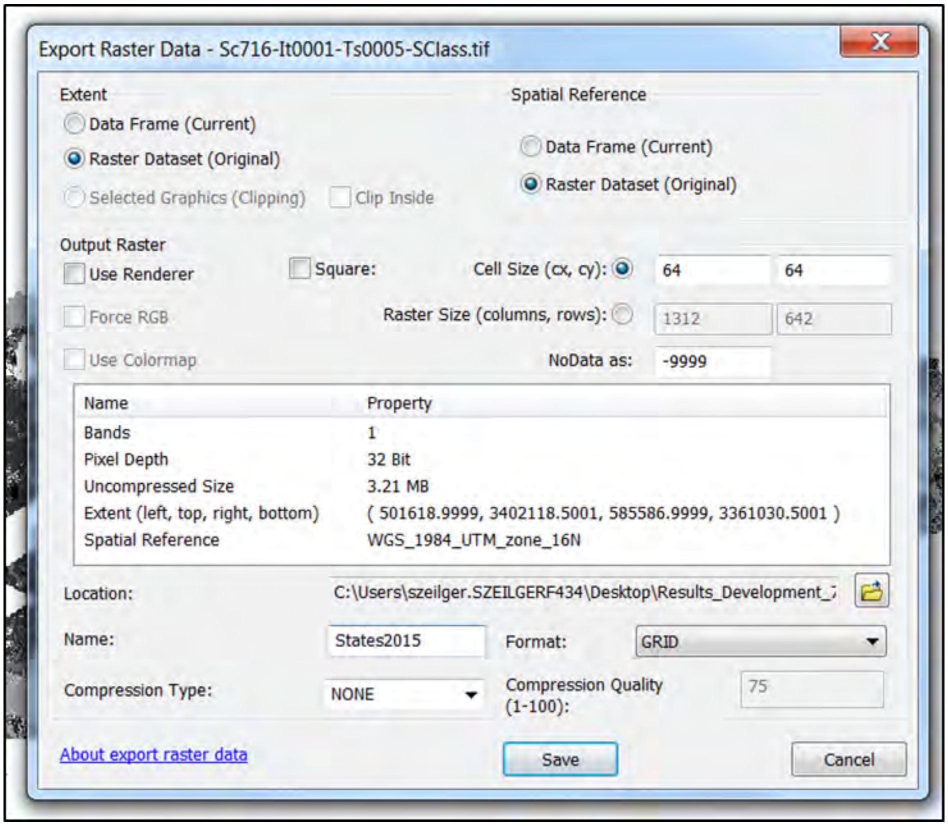
Figure D-1.14 An example of an age map that could be uploaded as the “Age file” under the “Initial Conditions” tab to run a spatially explicit model in ST-SIM. In general, this raster file (file type: Geo.TIFF) indicates the ages of all stands throughout the landscape. Although all landscape cells are given an age, stand ages are only relevant for landscape states where age influences the state identification or transitions (i.e., the Longleaf Pine states).

8.4 Viewing predictive output maps

Following a simulation in the ST-SIM landscape model, the resulting maps can easily be viewed and manipulated in ArcGIS or any other GIS platform. As described in *Section 4.5.3 Output Options*, predictive output maps are exported as Geo.TIFF files. These files can be opened within ArcGIS in this format without requiring any additional changes. However, in order to manipulate or to analyze these images using ArcGIS's ArcToolBox features, you can export the Geo.TIFFs as raster files by right-clicking on a Geo.TIFF's name in the ArcGIS Table of Contents, highlighting "Data", and selecting "Export Data".



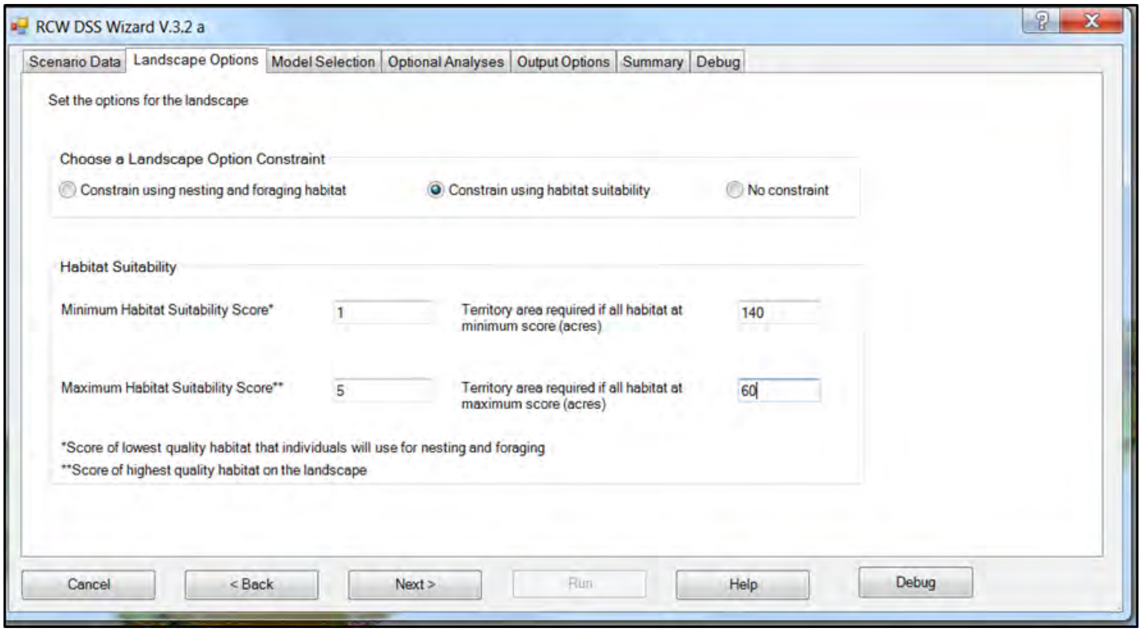
In the Export Raster Data window that appears, you can change the image's cell size (not recommended), browse to the location where the new raster layer should be saved, select "GRID" under the "Format" drop-down list, and name the new layer. Finally, you would click on "Save" to convert the Geo.TIFF to a raster file.



9. Integrating Results with the RCW Population Model

Detailed information pertaining to the RCW population model can be found in Walters et al. (2011) as well as in the report accompanying this user's guide. In this section, we will describe changes made to the RCW population model that allow the population model to consider habitat suitability maps produced through the ST-SIM landscape model as part of the RCW DSS.

In the RCW population model version 3.0, we included a tab for "Landscape Options", where the user can choose to constrain the availability of RCW territories (or cavity clusters) based on (1) nesting and foraging habitat area, (2) habitat suitability, or (3) no constraints. To use the population model within the RCW DSF, you would select the radio for "Constrain using habitat suitability".



With this option, the population model will determine whether existing RCW territories (i.e., those indicated in the initial cavity cluster layer), recruitment clusters, and buds have enough habitat to support an RCW group based on habitat suitability thresholds. Here, the user must indicate the "Minimum Habitat Suitability Score" and the "Territory area required if all habitat at minimum score" in acres in the adjacent boxes. These inputs, in other words, set how large a territory must be if it is composed entirely of low suitability habitat. For example, in the baseline ST-SIM landscape model for Eglin AFB, landscape suitability ranges from 1 (marginally suitable) to 5 (highly suitable; Figure D-1.3). Based on the actual density of RCW territories between 2000 and 2013 and the area/configuration of landcover types in 2001, we estimated that a territory would have to be large, at least 120 acres, if the habitat was of poor quality (i.e., if the area-weighted average habitat suitability for that territory was 1; see Appendix 3 in the accompanying report for more information on this calculation). Therefore, in this example, we would parameterize the model such that the Minimum Habitat Suitability Score = 1 and the Territory area required if all habitat at minimum score = 120 acres.

The user must also indicate how small a territory can be if that territory is composed entirely of highly suitable habitat in the boxes adjacent to "Maximum Habitat Suitability Score" and "Territory area required if all habitat at maximum score (acres)", respectively. Continuing with the example described in the previous paragraph, we estimated that a territory could be relatively small, approximately 70 acres, if habitat was of very high quality (i.e., if the area-weighted average habitat suitability for that territory were 5; see Appendix 3 for more information on this calculation). Therefore, in this example, we would parameterize the model such that the Maximum Habitat Suitability Score = 5 and the Territory area required if all habitat at maximum score = 70 acres.

When using the Habitat Suitability option, the user must also add one or more landscape state files created through the ST-SIM landscape model into the ArcGIS project (in addition to the initial landscape and RCW cavity cluster shapefiles). These additional landscape files must be in raster format with a 50 m cell resolution, have state identifiers identical to those used in the ST-SIM landscape model (*Section 4.1 Landscape states*), and have the same coordinate system as the initial input shapefiles required to start the RCW population model. Each landscape file name

must also end in "_t<time step>", where the value given in place of "<time step>" indicates the model time step at which point the new landscape map should be evaluated. For example, if the user added a raster named "Landscape_t5" to the ArcGIS project, then habitat suitability values would change to those associated with the landcover states in that raster at time step 5.

The user must also always provide a landscape state file for time step 1 (e.g., "Landcover_t1") to indicate habitat suitability at the start of the model. From there, any number of additional landscape state files can be added. For example, if the user includes the files "Landcover_t1", "Landcover_t5", "Landcover_t7", and "Landcover_t8" for a simulation with 10 time steps, suitability would initially be based on the state types given in "Landcover_t1", and the model would re-evaluate suitability at time steps 5, 7, and 8 based on the states given in "Landcover_t5", "Landcover_t7", and "Landcover_t8", respectively. The final 2 time steps of the simulation would continue to consider the suitability values associated with states given in "Landcover_t8".

Therefore, in summary, you would export the Geo.TIFF landscape state map used to start the ST-SIM landscape model as a raster file with a 50 x 50 m cell size (see *Section 8.4 Viewing predictive output maps*) and name the new raster file "<NAME>_t1". You would also export all predictive landcover state maps produced by a simulation of the ST-SIM landscape model as raster files (50 x 50 m cell size), naming these new files such that the file name ends in the time step that each landscape should be considered in the RCW population model. These raster landscapes should be added to your ArcGIS project, appearing within the ArcGIS Table of Contents to the left of the screen.

At the start of an RCW population model simulation utilizing the Habitat Suitability option, the model will create Theissen polygons around all initial territories and recruitment clusters, using the "Landcover_t1" landscape file to calculate an area-weighted suitability score for each territory within the confines of its Theissen polygon. In addition, using the user-specified minimum and maximum suitability scores and their associated territory areas, the model will use the formula for a straight line (Y = mX + B) to calculate threshold area values (Y, in acres) for every suitability score (X) between the minimum and maximum specified by the user (see Appendix 3 in the accompanying report). The model will then compare each territory's area with the calculated threshold area associated with its area-weighted average suitability score. If a territory's area is less than the threshold area required, the model assumes that the territory is not large enough or of high enough quality to support a group of RCWs, and no birds will be allowed to reproduce at that location. This process is repeated at each time step during which the landscape suitability layer changes.

In some simulations, a territory may support an RCW group at time step *t* but not at time step *t+1* due to changes in the territory's average suitability. In this case, all RCWs previously in that territory will become Floaters at time step *t+1*, and the territory will be removed as an option for occupancy by neighboring birds until the suitability improves. In contrast, a territory may be unsuitable and vacant at time step *t*, but, due to changes in the landscape, it may become suitable enough to support an RCW group at time step *t+1*. In this case, the newly suitable territory would have male and female breeding vacancies that could be filled by neighboring RCWs at time step *t+1*.

From there, the RCW population model operates as described in Walters et al. (2011) and in the report accompanying this user's guide. The model will ultimately make predictions of RCW occupancy, population size and composition through time, which are influenced by habitat suitability predictions made through the ST-SIM landscape model.

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E. Supporting Methodology

E1. Reference landcover maps for validation and modeling methodology

Staff at Eglin AFB provided us with a series of GIS datasets: (*i*) four maps classified from satellite imagery showing base landcover in 17 categories for the years 2001, 2003, 2007, and 2010; (*ii*) a map of ages for all forested stands throughout the base as of 2005; (*iii*) a map of the base showing the number of years since forested stands were last burned ("year since burn" data available for years 1986 to 2010); and (*iv*) a map of various stand characteristics for forested stands throughout the base. These maps were modified and combined in ArcGIS 10.2.2 (ESRI) to create reference landcover layers in raster format showing the amount and distribution of states recognized by the ST-SIM landscape model for the years 2001, 2003, 2007, and 2010. In the initial dataset processing for the GIS layers, we ensured that all layers were projected into the coordinate system "WGS 1984 UTM Zone 16N". Additionally, we converted all vector layers (i.e., the age, time since burn, and stand characteristic maps) to raster layers with a 30 m x 30 m cell size.

We then reclassified the landcover layer for each available year such that the original 17 landcover types were grouped into the 7 broad landcover classes recognized by the ST-SIM model (Table E1-1). We also created four stand age layers using the original 2005 stand age map. For each landscape cell in the age layers, we subtracted 4 years, subtracted 2 years, added 2 years, and added 5 years to the "2005 age" in order to create age layers in raster format for 2001, 2003, 2007, and 2010, respectively. For the 2007 and 2010 age layers, we assumed that no stand-clearing fires, development projects, or other landcover changes reverted a stand's age back to zero. However, such events could have occurred within the period 2005-2010, and we may have overestimated the ages of some stands (although we do not believe that this impacted simulation results, because such changes to the landscape would have altered the landcover state to a non-longleaf pine state where age is irrelevant).

Finally, to create the final landcover state layers, we added the modified raster layers together using the Map Algebra function in ArcToolBox (see Appendix D for details on this methodology). Under this protocol, the landcover layers allowed us to differentiate between the broad landcover state classes for Bare Land, Sand Pine, Developed areas, Water, Hardwood stands, Mixed (pine and hardwood) stands, and Longleaf Pine stands. We then categorized all landscape cells falling into the broad Longleaf Pine landcover class based on age and canopy BA using the age and stand characteristics layers, respectively. Finally, we used the information contained in the time since burn map to approximate midstory suitability and groundcover for all landscape cells falling into the Longleaf Pine landcover class. We assumed the following midstory and herbaceous groundcover characteristics based on the amount of time since a given Longleaf Pine landscape cell had been burned: (*i*) 0-15 years = High Midstory Suitability and High Cover, (*ii*) 16-20 years = Moderate Midstory Suitability and High Cover, (*iii*) 21-35 years = Moderate Midstory Suitability and Low Cover, and (*iv*) > 35 years = Low Midstory Suitability and Low Cover. Because we approximated midstory suitability and percent herbaceous groundcover in this manner, we could not account for the states contained within the ST-SIM model where midstory suitability is high and groundcover is low (i.e., the states typically resulting from mechanical midstory removal or herbicide application). Therefore, our reference layers for 2001, 2003, 2007, and 2010 did not contain the six landscape states representing this condition, which automatically resulted in < 100% accuracy for our predictive maps. The resulting landscape state layers 2001, 2003, 2007, and 2010 were resampled to have a 1 ac cell size and ultimately showed the area and distribution of the landscape states recognized by the

ST-SIM model. The areas of the broad landscape state classes for the reference maps are shown in Table 4 and Figure 12.

In addition, both the 2001 and 2010 reference landcover state maps were also used as the initial landscape layers in the ST-SIM landscape model and the RCW population model. For use in the ST-SIM landscape model, the 2001 and 2010 reference landscape state layers were converted to GeoTiff files using ArcToolBox in ArcGIS ver. 10.2.2 with a 1-acre cell size and the coordinate system "WGS 1984 UTM Zone 16N". We also converted the original age layers for 2001 and 2010 into GeoTiffs with the same resolution and coordinate system for use as the initial age maps for the ST-SIM landscape model.

For use in the RCW population model, we reformatted the original 2001 and 2010 landcover maps (created through a supervised classification of remotely sensed imagery) by converting them to polygon shapefiles using ArcToolBox. We then reclassified the original landcover classifications to landcover types recognized by the RCW population model (i.e., Hard, Mixed, Other, Water, Pine, and Pine Dispersal Only; Table D1-1). Finally, we added required columns for Stand ID ("STAND_ID"; text), Landcover Type ("TYPE", text), Pine Age ("PINE_AGE", double), and Stand Score ("Stand_Scor", double, optional) and populated these columns for each stand within the polygon landscape layer according to Table E1-1.

Finally, after initializing the ST-SIM landscape model with the reference layer for 2001, we simulated landcover change at Eglin AFB from 2001 to 2010 under baseline conditions (Appendix D). From this simulation, we produced predictive annual landscape state maps for this area over the 9-year study period. We compared the area and distribution of landcover states as predicted by this simulation for the years 2003, 2007, and 2010 with the same information contained in the reference landcover layers for corresponding years in order to validate the ST-SIM landscape model.

Table E1-1. Reclassification scheme for the original landcover maps provided by the staff at Eglin AFB. Original categories were reclassified into new landcover types recognized by (*i*) the ST-SIM model and (*ii*) the RCW population model.

Original Landcover Category (map value)	**ST-SIM Landcover Category**	**RCW Population Model Landcover Type**		
		Type	*Stand Age*	*Stand Score*
No Data	No Data	Other	0	1
Developed (1)	Developed	Other	0	1
Grassland[1] (2)	Bare Land[1]	Open	0	1
EF-Longleaf (3)	Longleaf Pine	Pine	60	5
EF-Sandpine (4)	Sandpine	Pine Dispersal Only	15	3
EF-Mixed (5)	Mixed	Mixed	0	1
SS-Evergreen (6)	Mixed	Mixed	0	1
SS-Mixed (7)	Mixed	Mixed	0	1
Bare Land (8)	Bare Land	Open	0	1
Emergent Vegetation (9)	Young Pine	Pine Dispersal Only	15	3
BLF-Evergreen (10)	Hardwood	Hard	0	1
BLF-Deciduous (11)	Hardwood	Hard	0	1
BLF-Mixed (12)	Hardwood	Hard	0	1
BLF-SS (13, 14)	Hardwood	Hard	0	1
Mixed Forest (deciduous, evergreen, scrub; 15)	Mixed	Mixed	0	1
Water (16)	Water	Water	0	1
Shoreline and Bare Land (17)	Bare Land	Open	0	1

[1]At Eglin AFB, the majority of areas classified as "Grassland" are open test ranges for military training. As such, they are maintained as opened areas that would never experience succession, and we accordingly classified these areas as "Bare Land".

E2. Methodology used to determine minimum area-suitability thresholds
These thresholds are specific to Eglin AFB and are a required parameter under the "Habitat Suitability Landscape Option" in the RCW population model.

If the user wishes to consider habitat suitability as a constraint on RCW cavity cluster excavation and occupancy or to operate the RCW DSS, coupling the ST-SIM landscape model with the RCW population model to consider a dynamic landscape throughout the course of a simulation, he/she should select the second radio button for "Constrain using habitat suitability" (Figure 16). With this option, the model will determine whether existing RCW territories (i.e., those indicated in the initial cavity cluster layer), recruitment clusters, and buds have enough habitat to support an RCW group based on habitat suitability thresholds.

Under this option, the user must indicate the "Minimum Habitat Suitability Score" and the "Territory area required if all habitat at minimum score" in acres in the adjacent boxes (Figure 16). These inputs, in other words, set how large a territory must be if it is composed entirely of low suitability habitat. The user must also indicate how small a territory can be if that territory is composed entirely of highly suitable habitat in the boxes adjacent to "Maximum Habitat Suitability Score" and "Territory area required if all habitat at maximum score (acres)", respectively. During the course of a simulation in the RCW population model, the model will use the formula for a straight line (Y = mX + B) to calculate threshold area values (Y, in acres) for every suitability score (X) between the minimum and maximum specified by the user. We refer to these as "area-suitability thresholds".

We determined appropriate area-suitability thresholds for RCW cavity clusters at Eglin AFB using the locations of actual RCW cavity tree cluster centers on the base from 2000 to 2013 and the 2001 reference landcover state map for the base. Because the actual area and shape of the cavity tree clusters was not recorded during population monitoring efforts, we estimated this information by starting a simulation of the RCW population model. To create the initial cavity tree cluster layer to parameterize the model, we used geographic coordinates for known RCW territory centers at Eglin AFB from 2000 to 2013, a total of 521 territories, contained in an existing database. This database was collated during an ongoing project at Eglin AFB that spanned the years 1990 to 2013 inclusive (Walters, unpublished data; see Walters et al. 1988 and Walters 2004 for population monitoring methods). The 2001 reference landcover state map was converted to a polygon shapefile and further processed for use as the initial landscape layer in the RCW population model (Appendix E1). We began a simulation in the RCW population model using these layers, saving the shapefile of Thiessen polygons around each cavity tree cluster center that the model automatically creates at the start of a simulation. We used these Thiessen polygons to represent the actual shapes and areas of known RCW territories.

We then converted the 2001 reference landcover state map to an associated habitat suitability map by creating a column in the raster layer's attribute table for habitat suitability value (Figure 7) and converting the layer's main cell values to habitat suitability using the "Lookup" tool in ArcToolBox, ArcGIS v. 10.2.2. We overlaid the Thiessen polygon layer onto the habitat suitability raster and used the Geospatial Modeling Environment (Beyer 2012) to calculate the area and the area-weighted suitability value for each Thiessen polygon (which represents individual RCW territories).

We then associated each RCW territory with an area category (in 10-acre increments) and an area-weighted suitability value rounded to the nearest whole number. After visually inspecting this information in table-form (Table E2-1), we determined that (*i*) an RCW territory with an area-weighted average suitability score of 1 should be a minimum of 120 acres to

support a group of RCWs and (*ii*) an RCW territory with a suitability score of 5 should be at least 70 acres. Note: we assumed that a suitability value of 1 was still at least marginally usable for RCW foraging and nesting because some of the observed RCW territories (32 territories) had area-weighted averages of 1. However, if the user employs a suitability range where the lowest value in the range is absolutely not usable for foraging and nesting by RCWs, then the lowest suitability value used to parameterize the model as the "Minimum Habitat Suitability Score" (here, 1) would not be the lowest value in the suitability range.

These values could be reasonable baseline parameters for any model of the RCW population at Eglin AFB. We will also explore the use of more conservative suitability thresholds (e.g., minimum: suitability 3, 120 acres; maximum: suitability 5, 100 acres) in simulations prior to the publication of our results. If the user employs a different suitability range (e.g., 1-10 instead of 1-5) or plans to model the RCW population at a different location, he/she can follow these guidelines to determine appropriate area-suitability thresholds for that model.

Literature Cited

Beyer, H. 2012. Geospatial Modelling Environment (software; http://www.spatialecology.com/gme).

Appendix E2-1. The number of observed RCW territories (2000-2013) at Eglin AFB with each combination of area (acres) and area-weighted habitat suitability score (associated with the ST-SIM landcover states; Appendix D; Figure 7).

Area (acres)[1]	**Area-Weighted Average Habitat Suitability Score (rounded to nearest whole-number)**				
	1	*2*	*3*	*4*	*5*
< 70	0	0	0	0	0
70-80	0	0	0	0	2
80-90	1	0	0	2	4
90-100	0	0	1	5	4
100-110	0	0	4	11	9
110-120	0	3	1	11	6
120-130	2	2	16	14	9
130-140	2	9	7	16	7
140-150	3	12	13	29	6
150-160	6	9	18	20	8
160-170	6	13	27	23	6
170-180	2	15	17	15	3
180-190	4	11	16	16	3
≥ 190	6	17	26	22	0

[1]Area ranges are greater than or equal to the first number in the range and less than the second number. For example, a territory belonging to the 70-80 acre size category must be ≥ 70 but < 80 acres.